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β1-Indexing®: Making Financial Simulation Relevant in Practice

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ABSTRACT

A successful long-term financial plan depends on the correspondence of projected returns and actual returns. Simulation results are subject to the effects of differences between implementation fund(s) attributes and asset class attributes used in the simulation. Thus, simulation outcomes and portfolio outcomes may be materially different. We would like to know that if the forecasted returns in our simulations are correct, the actual returns will be the same as the forecasted returns. β1-Indexing® addresses these issues with a guideline that uses reasonably available information: Best-Fit β and R squared. β1-Indexing® and Beta1-Indexing® are registered trademarks of Vernon V Chatman III, CFP®.

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To begin, a number of professional advisors hate Monte Carlo analysis and other financial projections. Their reasons for doing so boil down to: the advisor will allow the client to become complacent or themselves become so. While this may be true; blame the advisor, not the simulation. Advisors want the client to believe in the plan they have developed and the simulations help them get that belief. On the other hand, the advisor does not want the blame when things do not go as projected. 'Haters' believe simulations are used to encourage investors "to ignore calamity and focus on the most probable outcomes" (Barrett, 2019). Exactly. Clearly, the advisor does not want the investor to focus on calamity and ignore the most probable outcomes. Things are not that binary. It is part of the 'advice' in 'advisor' for the planner to stress-test plans and to develop, with the client, resilience strategies. A clear but extreme example is estate planning (wills, trusts, life insurance, long term care, etc.). So, if we are planning, forecasting the future is unavoidable.

I suspect it has always been true that some advisors and investors endeavor to 'beat the market.' They seek a recipe of 'secret sauces' for excess return. This in the face of the inability, with precision, to predict the market itself (there is much evidence that over time active investors fail to even match the market). An objective of 'beat the market' has no particular utility; it ignores risk and reduces financial planning to a singular goal which may be at odds with client best interest. Most clients have multiple goals and differing risk tolerances with respect to those goals. Further, 'beat the market' endeavors rest upon an unstable foundation since they lack assurance that the actual portfolio implementation assets have a (stable) known relationship to the market (measure/benchmark used). Thus, absent such assurance, even if you correctly predicted the market, you are not assured of matching or beating the market with the actual portfolio. So, as a minimum, we need evidence that if our financial (market) (simulation) forecasts are correct, our financial plan (implementation) results will be the same as our forecast. That way, if we get the market forecast (simulation) right, we have assurance that our actual portfolio will reflect that.

β1-Indexing® does not tackle the problem of correctly simulating the market, but instead addresses the more modest problem of seeking assurance that our implementation outcome will match our simulation outcome, ***if*** our simulation is correct. We know simulation outcomes and portfolio outcomes may be materially different (Tokat et al., 2006):

> [when] analysis models asset classes, not investment products [or indexes,] . . . the actual experience of an investor in a given investment product (e.g., a mutual fund) may differ from the range of projections generated by the simulation, even if the broad asset allocation of the investment product is similar to the one being modeled. (Parrish, 2019)

A *β1-Indexing*® approach takes advantage of reasonably available information, Best-Fit *β* and R-squared (Eyssell, 2003), in a guideline that can be used to reduce investing complexity (Chatman, 2007). When using financial simulations (models) with clients, using this same guideline can help determine whether the models are relevant to the portfolios used. Using it can also help identify the parts of portfolios where there are exposures relative to the model. While this guideline is not mechanistic, it provides objective factors for choosing funds. A *β1-Indexing*® approach will not necessarily lead to either higher portfolio returns or, by itself, create rules for making estimates of future returns. *β1-Indexing*® helps make implementations simpler and more synchronous with a model/simulation and thus makes the model/simulation more relevant and its predictions more verifiable. A defining characteristic of scientific models is that they make falsifiable or verifiable predictions; the relevance and specificity of those predictions determine how potentially useful the model is. A *β1-Indexing®* approach can help the financial planning profession become more scientific.

Model Implementation

Table 1 illustrates certain aspects of investment decision-making. A number of the factors shown may be found in Monte Carlo financial simulation software. These and other different factors may be involved with other simulation techniques. *β1-Indexing®* does not eliminate the need to forecast such values. Table 1 is not intended to be a recommendation of a portfolio.

Asset Class	Asset Class Proxy/Benchmark	Index Fund	Expected Return	Expected Risk/SD	Yield/ Interest	Dividend	Turnover	Holding Limits Min;Max	Correlation
US Large Cap	Standard & Poor's 500 TR	VFINX§ ß=1.00 r^2=100	Aa%	Bb%	Cc%	Dd%	Ee%	Mn1%; Mx1%	C1
US Small Cap	Russell 2000	NAESX§ ß=1.00 r^2=99.71	Ff%	Gg%	Hh%	Ii%	Jj%	Mn2%; Mx2%	C2
Fixed Income	BarCap US Agg Bond TR USD	FBIDX§ ß=0.93 r^2=98.22	Kk%	Ll%	Mm%	Nn%	Oo%	Mn3%; Mx3%	C3

§Funds used are examples and are not recommendations.
Table 1.

Table 1 does not show numeric values for a variety of factors specifically to avoid debate about the correctness of those values. For purposes of this article, assume the factors are accurately and exactly forecast for the relevant indexes. This allows us to focus on the correspondence of projected values and implementation actual values. Although Table 1 shows three asset classes, *β1-Indexing® does not prescribe the number of asset (sub)classes, which benchmark Index(es), or which asset classes to use in portfolio construction. Benchmarks used may be cap-weighted, as here, or not; that is not the issue in this discussion.* Investment in each asset class uses actual assets.

Clearly, to the extent the actual assets used to implement a portfolio based on the above model do not behave in alignment with the benchmark index used, a simulation will not reflect the real portfolio's performance. To enhance the value of simulations we desire means of assurance that if our projections are correct, the implemented portfolios will behave like our projections. This applies whether our projections are short-term (one month) or long-term (more than 5 years).

Fundamental to modern approaches to investing is the view that diversification is a desirable attribute of a well-designed portfolio. Another side of this perspective is that (subsets of) assets inside an asset class behave such that their behavior as a group can be predicted (with acceptable ranges of error). We know asset class members do not behave exactly the same all of the time. Thus, we would not automatically expect an accurate forecast/simulation of the behavior of asset *X* in asset class *C* to be an accurate forecast/simulation of asset *Y* (also in asset class *C*). However, we would expect a forecast/simulation of the behavior of asset *X* to be accurate for asset *Y* to the extent *Y* is 'like' *X*. *Implementation assets (in aggregate) in a portfolio's asset class need to behave 'like' the model's parameters for the asset class in order* *for the model to be considered useful for investment guidance with respect to that implementation.* Expressed more generally, without *β1-Indexing*® (i.e., using index mutual funds or exchange traded funds that exactly model the benchmark/index/bogey) there is a logical distinction between the implementation asset set and the benchmark (see Table 1, rows 2 through 4, columns 2 and 3). We have to be concerned with the properties of the implementation asset set (for example, index mutual fund) as well as the benchmark (for example, an index). There are also logical problems, such as division.

Figure 1 shows variation within an asset class:

Fund Name	Best Fit Index	Symbol	3-Year Return (%)	Mean	Standard Deviation	Best Fit Beta	Best Fit R-Squared	Expense Ratio (%)	▲Min Initial Purchase ($)	Index Funds
Fidelity® Series International	MSCI EAFE NR USD	FINVX	7.28	0.57	16.82	1.00	94.54	0.85	0	No
Fidelity® Series International	MSCI EAFE NR USD	FFVNX	7.49	0.59	16.82	1.00	94.69	0.67	0	No
Goldman Sachs Focused Intl Equ	MSCI EAFE NR USD	GIRNX	8.49	0.66	16.14	0.95	93.79	1.20	0	No
Goldman Sachs Focused Intl Equ	MSCI EAFE NR USD	GSISX	8.12	0.63	16.18	0.96	93.74	1.56	0	No
Goldman Sachs Intl Eq Insights	MSCI EAFE NR USD	GCITX	7.52	0.58	16.88	1.01	95.65	1.04	0	No
Goldman Sachs Intl Eq Insights	MSCI EAFE NR USD	GCISX	6.96	0.55	16.88	1.01	95.75	1.39	0	No
Goldman Sachs Strategic Intl E	MSCI EAFE NR USD	GSTKX	8.63	0.65	16.33	0.98	96.62	1.22	0	No
MassMutual Select Diversified	MSCI EAFE NR USD	MMZLX	6.61	0.51	17.62	1.06	96.94	1.17	0	No
MassMutual Select Diversified	MSCI EAFE NR USD	MMZSX	7.08	0.54	17.55	1.06	96.90	0.99	0	No
MassMutual Select Diversified	MSCI EAFE NR USD	MMZYX	6.80	0.53	17.74	1.07	96.82	1.09	0	No
Oppenheimer International Valu	MSCI EAFE NR USD	QIVYX	6.28	0.50	16.67	0.97	91.56	0.90	0	No
Optimum International Instl	MSCI EAFE NR USD	OIIEX	6.47	0.49	15.13	0.91	95.91	1.36	0	No
Principal International Equity	MSCI EAFE NR USD	PIIPX	8.24	0.63	16.33	0.99	98.20	0.74	0	Yes
Principal International Equity	MSCI EAFE NR USD	PIIQX	8.38	0.64	16.31	0.99	98.18	0.62	0	Yes
PIMCO Intl StkPLUS® AR Stra (U	MSCI EAFE NR USD	PPUDX	11.69	0.91	17.69	1.06	96.43	1.04	1,000	No
SSgA International Stock Selec	MSCI EAFE NR USD	SSAIX	7.30	0.58	17.33	1.04	96.75	1.00	1,000	No
Columbia Overseas Value Z	MSCI EAFE NR USD	COSZX	8.98	0.68	16.05	0.96	95.43	1.21	2,000	No
Dreyfus Intl Stock Index	MSCI EAFE NR USD	DIISX	8.45	0.66	16.66	1.01	99.10	0.60	2,500	Yes
INTECH International T	MSCI EAFE NR USD	JRMTX	8.55	0.67	16.14	0.95	92.72	1.26	2,500	No
BNY Mellon International Inv	MSCI EAFE NR USD	MIINX	8.27	0.65	17.13	1.03	97.45	1.30	10,000	No
BNY Mellon International M	MSCI EAFE NR USD	MPITX	8.55	0.68	17.07	1.03	97.47	1.05	10,000	No
BNY Mellon Intl Appreciation I	MSCI EAFE NR USD	MARIX	7.59	0.60	16.62	1.01	98.19	1.08	10,000	No
BNY Mellon Intl Appreciation M	MSCI EAFE NR USD	MPPMX	7.85	0.62	16.62	1.01	98.09	0.83	10,000	No
Vanguard Developed Markets Idx	MSCI EAFE NR USD	VTMGX	8.91	0.69	16.43	1.00	98.35	0.09	10,000	Yes

Data updated through 06-13-14 Click the button to change screening criteria.

Your Screen (EmergingMarkets-MSCI_EM) Summary: Save Criteria

(Redemption Fee = 0)
and (No-Load Funds = Yes)
and (Best Fit Beta (3 Year) >= 0.9)
and (Best Fit Beta (3 Year) <= 1.1)
and (Best Fit R-Squared (3 Year) >= 90)
and (Best Fit Index = MSCI EAFE NR USD)
and (Minimum Initial Purchase <= 10000)

Figure 1. Morningstar.com Screen

Variation raises the issue of which fund(s) to use in an asset class in a portfolio. The general difficulty here is that without *β1-Indexing*® we need to determine, project, and monitor the historical and future attributes of at least two distinct sets of assets per asset class ([1] the implementation asset set and [2] the benchmark): for example, MSCI EAFE NR USD Index and VTMGX and/or PPUDX (remember the objective is exactness of actual outcome to forecast). Thus, for the “portfolio” in Table 1, there are a minimum of 18 attributes to deal with instead of 9 (see Table 1, columns 4, 5, and 10). This makes financial planning complex. For complex problems it usually helps to reduce the number of factors that have to be dealt with to reach a reasonable or correct solution.

Portfolio Returns

Brinson et al and others have argued that "approximately 90 percent of the variability of a fund's return across time is explained by the variability of policy returns" (Ibbotson and Kaplan, 2000). This finding is often misinterpreted to mean that merely having a diversified portfolio is the primary goal and obtains the investor most of [90% of] the return of the asset classes used--fund selection within asset class is of limited importance. Even if this misinterpretation was correct, it clearly tells us that we need to deal with two returns (policy return and active return). A *β1-Indexing®* approach allows us to only deal with one return, making fund selection critical.

With Modern Portfolio Theory (MPT), making projections for expected return (ER), standard deviation (SD), and other factors is critical. When we use Monte Carlo simulation planning tools these factors are key inputs. Any simulation (Monte Carlo or not), depends upon the 'likeness' of the implementation asset(s) behavior to that of the model factors. Furthermore, some indexes (or asset sets) that one might want to use as benchmarks for portfolio construction do not have mutual funds or ETFs that exactly model them. For investment advisors attempting a *β1-Indexing®* approach, an index with mutual funds or ETFs that exactly model it has added value over one that does not. A key benefit of using *β1-Indexing®* in (Monte Carlo) simulations is that we only have to predict model factors (e.g., ER, SD, and so on for Monte Carlo) for one set of securities.

As Best-Fit β diverges away from (above or below) 1, an index is less meaningful as a proxy or benchmark. The use of high and low β proxies (implementations) may have been justified in the past by the cost of investing in a large basket of securities; however, with today's low-cost index mutual funds and exchange traded funds (ETF), that time has passed. New approaches can now be used for asset selection for portfolio implementation. In what follows I will use the term 'index' to refer to benchmarks used in models, but this includes any asset set used as a model's benchmark(s) not just formal indexes.

Asset Selection

An index one might want to use as a stand-in for an asset class might not have a mutual fund or ETF that exactly models it, so the question arises as to how to select a fund to use (see Figure 1). One choice is to define a new index that permits *β1-Indexing®* using a fund that is available. Another choice is simply not to invest in that asset class. Additionally, one might simply choose a different index that enables *β1-Indexing®*. In theory, those options are fine, but as a practical matter, currently they do not seem to be the most likely possibilities. It may be that in time *β1-Indexing®* will be possible using the preferred index.

Let us examine Figure 1 using what we know. Cost is a significant driver of final value (Barker, 2021). The amount available to invest as well as the allocations used in a portfolio can restrict possible fund choices and therefore cost options. For example, if we need 10% in International, unless we have at least $100,000 to invest VYMGX is not an option although its expense ratio is only .09%. Furthermore, we need to consider whether the expense level is likely to endure for our time horizon. We know that at a given Best-Fit β a higher R-squared is to be preferred. We also know that Best-Fit β closer to 1 is to be preferred over lesser or higher Best-Fit β with the same R-squared. At a theoretical level with *β1-Indexing®*, because the implementation asset set and bogey asset set are identical, there is no 'will the future be like the past' issue for Best-Fit β and R-squared; however, at least currently, using a *β1-Indexing®*

approach using likely indexes, planners are not absolved of responsibility to consider this issue when selecting funds for a portfolio.

Using Best-Fit β and R-squared, the selection guide for portfolio candidates is: use the available fund (as constrained by any required minimum initial investment, client funds available, and allocation percent) that has Best-Fit β closest to 1.0 with R-squared closest to 100 percent; where available funds have “similar”/same Best-Fit β and R-squared, depending on the difference, choose the fund with the lowest cost. If for all available funds R-squared is too low for Best-Fit β to be meaningful, bypass using that index or asset class. Although this approach is not mechanistic, it does allow identification of objective factors for choice using reasonably available information. This guideline can be used to create a pool of funds from which to choose. Of course, past performance does not guarantee future performance and the planner must evaluate the likelihood the fund(s) performance will continue. This guideline will tend to favor picking index funds because they employ methodologies that explicitly attempt to model the index (are not closet index funds). This pool contains funds that behave ‘like’ the index. Depending on the degree of correspondence we can reach *a priori* judgments regarding whether simulation parameters, if correct, can be expected to be reflected in realized outcomes.

The above guideline applies for the general case and can be used in conjunction with the following *β1-Indexing®* ratings:

Code	Rating	R^2, Best-Fit **Beta**	Expense Ratio %	Redemption Fee	Load
β1-Id	β1-Indexing® Diamond	$R^2 = 100, \beta = 1.00$	≤ .1	0	0
β1-Ig	β1-Indexing® Gold	$R^2 \geq 98, \beta \leq 1.02, \beta \geq .98$	≤ .2	0	0
β1-Is	β1-Indexing® Silver	$R^2 \geq 97, \beta \leq 1.03, \beta \geq .97$	≤ .3	0	0
β1-It	β1-Indexing® Titanium	$R^2 \geq 96, \beta \leq 1.04, \beta \geq .96$	≤ .4	0	0
β1-Ib	β1-indexing® Bronze	$R^2 \geq 95, \beta \leq 1.05, \beta \geq .95$	≤ .5	0	0
β1-I*	β1-Indexing® Star	$R^2 \geq 90, \beta \leq 1.10, \beta \geq .90$	≤ .5	0	0
β1-Ij β1-Iα	β1-Indexing® Junk β1-Indexing® Alpha	Not ratable as Star, Bronze, Titanium, Silver, Gold, or Diamond			

Table 2. *β1-Indexing®* Ratings

The ratings classify quality of fit and expense (Carlson, 2013). These ratings are not a substitute for judgment. Their purpose is to help one focus on exposures relative to potential differences between simulations and actual outcomes assuming a fund is expected to behave as it has in the past and/or this is what is projected for its future behavior. *β1-Indexing®* does not instruct on rules for making projections. Implementing a portfolio using funds for an asset class that (in aggregate) would be classified (and/or forecast) as Alpha/Junk means simulations using that asset class' proxy/benchmark index’s projected performance is likely misleading.

Consider the following composite benchmark:

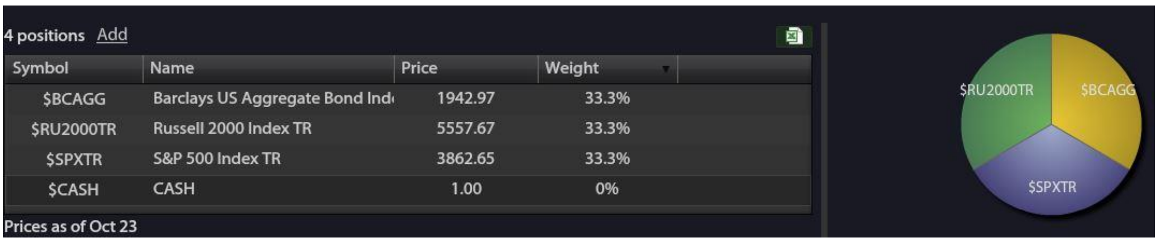

Figure 2.

We can test the efficacy of the *β1-Indexing*® ratings by considering a back-test using funds with a Gold or better rating:

Best Fit Index	Ticker	Best Fit Beta	Best Fit R-Squared	Annual Report Gross Expense Ratio	Prospectus Gross Expense Ratio	Index Fund
S&P 500 TR USD	LOGIX	0.83	85.42	1.300	1.310	No
Barclays US Agg Bond TR USD	TAIBX	0.93	89.95	0.780	0.730	No
Russell 2000 Growth TR USD	VRTGX	1.00	100.00	0.080	0.080	Yes
Barclays US Agg Bond TR USD	DBIRX	1.01	99.83	0.160	0.160	Yes
Russell 2000 TR USD	DXRLX	2.00	100.00	1.350	1.350	Yes
S&P 500 TR USD	FUSEX	1.00	100.00	0.100	0.100	Yes

Figure 3.

With these constraints, we see that there is a good fit of implementation to benchmark.

Figure 4.

This means that if the funds continue to perform according to their rating then, *if* the forecasted returns in our simulations are correct, the actual returns will be very much the same as the forecasted returns. In contrast, if we implement using funds with Junk ratings we get very different results from a back test.

The results from the *β1-Indexing*® - Junk back test appear to provide a much greater return than the Gold rated portfolio, however, this portfolio has a much different risk profile than our benchmark and thus may be adverse to client best interest:

	1 year	3 years
Annualized Total Return		
Beta1-Indexing Benchmark	5.5%	10.9%
Beta1-Indexing - Best	6.6%	11.3%
Beta1-Indexing - Junk	**7.1%**	**14.6%**
Risk (standard deviation)		
Beta1-Indexing Benchmark	**7.2%**	**7.6%**
Beta1-Indexing - Best	7.8%	7.6%
Beta1-Indexing - Junk	10.6%	11.4%
Alpha		
Beta1-Indexing Benchmark	-0.4%	-0.2%
Beta1-Indexing - Best	1%	0.3%
Beta1-Indexing - Junk	-1.2%	-1.2%
Beta		
Beta1-Indexing Benchmark	0.59	0.72
Beta1-Indexing - Best	0.64	0.71
Beta1-Indexing - Junk	0.80	1.02
Sharpe ratio		
Beta1-Indexing Benchmark	-0.29	1.22
Beta1-Indexing - Best	**-0.08**	**1.27**
Beta1-Indexing - Junk	-0.33	1.08

12-month Yield: Beta1-Indexing - Best: 1.9% Beta1-Indexing - Junk: 0.88%

Assumptions:

Dividends: Beta1-Indexing Benchmark: reinvested; Beta1-Indexing - Best: reinvested; Beta1-Indexing - Junk: reinvested

Rebalancing: Quarterly

The benchmark used to calculate alpha, beta is: S&P 500 Index TR

Figure 5.

Conclusion

The use of Best-Fit β and R-squared provides objective measures for selecting amongst funds. The asset weighting issue (risk tolerance) is a matter for another discussion. A *β1-Indexing*® approach and use of *β1-Indexing*® ratings can assist in evaluation of the relevance of simulations by aiding our desire for means of assurance that if our projections are correct, the implemented portfolios will behave like our projections (have similar returns and risk profiles). This assists in a more rigorous evaluation of portfolio models and planning outcomes.

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Chatman III, V. (2007) 'β1-Indexing™: Reducing Investing Complexity', *Journal of Financial Planning Between the Issues*, September http://vchatman.com/beta **(**Accessed 10 January 2021). A passive ETF could be a pure example of β1-Indexing® in that its holdings exactly match the components of its benchmark index. In fact, the ETF might be created from (the definition of) the index. We can use Beta and R-squared with respect to that index to evaluate how well the management of the ETF succeeds in behaving like the index. Morningstar uses the term 'Strategic Beta' "to highlight … a group of index-linked investments, all of which have the goal of achieving a beta equal to one as measured against their benchmark indexes" (*The Strategic Factor of Smart Beta*, Ben Johnson, 10 April 2010 http://vchatman.com/beta [Accessed 10 January 2021]) R-squared does not seem to be a factor in this classification.

Eyssell, T. (2003) 'What's the Proper Beta? Financial Advisors and the "Two-Beta Trap"', *Journal of Financial Planning*, September pp.54-57. See also, http://www.morningstar.com/InvGlossary/best_fit_beta.aspx (Accessed 18 May 2020). Additionally, Tracking Error, essentially the volatility of the differences in returns, is not generally as readily available as Best-Fit β and R-squared measures. Further, R-squared does not seem to play a role in evaluation using tracking error. A stable difference in return does not mean a forecast for (benchmark) *Index* is the same return for *Asset* with low tracking error. So, portfolio performance will differ.

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