Allocation of Wealth Both Within and Across Goals: *A Practitioner's Guide*

Franklin J. Parker

Franklin J. Parker
is chief investment officer at Bright Wealth Management, Dallas, TX.
franklinjamesparker@gmail.com

KEY FINDINGS

- Recent breakthroughs in goals-based portfolio theory now direct how wealth should be rationally divvied across goals, as well as how wealth should be allocated to investments within goals. This discussion is a "how to" for practitioners operating in a goals-based setting.
- Goals-based wealth allocation results in higher probabilities of goal achievement relative to mean-variance optimization. Though mean-variance portfolio allocation can be adapted to a goals-based context, it yields lower probabilities of goal achievement.
- There are numerous implications for the industry under a goals-based paradigm. High-variance, low-return investments may yet play a role in portfolios, the line between investment manager and advisor is now fuzzier, and the regulatory ossification of mean-variance portfolio theory creates hurdles for goals-based practitioners.

ABSTRACT: *Although the goals-based investment literature has grown, there remain two unsolved problems. First, there is no cohesive theory for the allocation of wealth across goals. If, for example, a client wants to retire in thirty years, send a child to university in eight years, and buy a vacation home in four, how she should divvy her wealth across those goals has been an open question. Restating the same problem: The vesting of shorter-dated goals carries a loss of achievement probability for longer-dated ones. How much probability loss is acceptable? Second, mean-variance portfolios yield lower probabilities of goal achievement than goals-based portfolios. I demonstrate use of the goals-based method. Parker (2020) introduced a cohesive goals-based allocation model that solves these problems. The approach, however, carries some practical challenges that are addressed in this discussion. Finally, I discuss some possible implications of the approach on the structure of firms, the regulatory environment, and the industry as a whole.*

TOPICS: ***Wealth management, behavioral finance, portfolio theory, portfolio construction****

Although goals-based investment theory has grown a rich literature, there are two conspicuous holes.

First, there is no cohesive theory for the allocation of wealth across goals. Investors regularly face multiple goals over varying time horizons, all competing for funding from a limited pool of wealth. If, for example, my client wants to retire in thirty years, send her child to university in eight years, and buy a vacation home in four years, I cannot offer direct advice for how to best allocate her wealth across those goals. How much of her wealth should she dedicate to her child's education? Resources spent there will necessarily reduce her probability of retirement, which is certainly more important.

When it is time to vest a shorter-dated goal—such as her vacation home—can that be done with an acceptable loss of achievement probability for her education and retirement goals? What *is* an acceptable loss of achievement probability? Currently, there are no straightforward answers.

Brunel (2015) offered a clever insight that delivered a partial solution to this problem. In the work of Das et al. (2010), which merged the goals-based aspects of behavioral portfolio theory (BPT) with mean-variance theory, an investor declares the maximum probability of failure she is willing to accept for a goal (which is converted into a risk-aversion parameter and optimization proceeds in via the traditional mean-variance method). As Brunel observed, and Parker (2020) demonstrated more formally, the declaration of a maximum failure probability threshold for a goal is mathematically synonymous with the declaration of a minimum wealth allocation to that goal. The insight of Brunel's model is to simply make the minimum wealth allocation the goal's allocation. It is a simple and effective solution.

There is a shortcoming to this approach, however. After the initial allocation, the client either has money leftover or not enough to go around. In either case, the solution is had through client conversation and subsequent adjustment. Although I certainly do not advocate for the abandonment of client conversation, the lack of a cohesive and continuous solution is indicative of the heuristic nature of the approach. Firmer theory should only serve to augment client conversation, and thus augment the results we can deliver.

The second hole is that, despite its importance, the synthesis work of Das et al. (2010) pushed goals-based portfolio theory backward in one critical way. Rather than maintain the more flexible risk-is-failure-probability of BPT, Das et al. (2010) restored the rigidity of mean-variance theory. This can be seen most clearly through solutions dubbed *infeasible* in their framework. There is only one class of infeasible solution; it occurs when the client has specified a failure probability threshold that is too low relative to the wealth dedicated to the goal. This results in a required portfolio return that is greater than the expected portfolio return at the endpoint of the efficient frontier.[1] In other words, when no possible efficient portfolio exists to meet the required return, the solution is considered infeasible.

[1] There are other critiques to the framework, discussed in Parker (2020).

Of course, the endpoint of the efficient frontier has generally been considered the endpoint of prudent investing. Beyond the last portfolio of the frontier is the realm of gamblers and hopefuls—certainly not respectable territory for financial advisors! Although I realize that it may sound absurd, I argue that this investment wilderness may yet hold promise. To illustrate my point, consider the unfortunate man who borrowed \$10,000 from a violent Mafia loan shark. He has full repayment due in the morning, but he has only \$7,000 tonight. As he makes his way into a casino, he is stopped by a religious missionary who offers him \$1,000 if he does not gamble. What should he do? What should we, his financial advisors, advise him to do? What is the rational choice?

Parker's (2020) goals-based utility (GBU) fills both of those theoretical gaps. GBU yields a mechanism to allocate across goals. We can now better understand whether the vesting of one goal carries an acceptable loss of achievement probability for another goal. Indeed, GBU allows us to analyze the substitution of one goal for another. GBU also resurrects the probability-maximization framework of BPT. Although this typically results in mean-variance efficiency, it is not always so. I argue that this is a fundamental feature of the GBU framework, though some will likely declare it a bug.

GBU, however, delivers some challenges to the practitioner. Namely, the model is recursive—the allocation of investments depends on the allocation across goals, which is itself dependent on the allocation of investments. There are some unfamiliar computational challenges as the goals-based model is centered around probability maximization, rather than familiar mean-variance optimization. Finally, there is the practical problem of soliciting relative goal values—not as straight forward as advertised. It is my aim to offer some solutions to these problems and to generally familiarize practitioners with the approach.

I begin with a quick review of the model. From there I discuss a possible goal-value solicitation mechanism. Then the discussion progresses to demonstrate a computational solution to the inherent recursion of the model, showing how one may arrive at an optimal allocation of wealth both across goals and across investments. Because many investors are mean-variance constrained, I also adapt the across-goal allocation model to work within mean-variance constraints. I then proceed to demonstrate, through an example, how the goals-based model responds to the evolution of goals through time. Finally, I delve into some real-world implications of the model and how it may push firms, the industry, and regulators toward a different structure.

On a personal note: I am myself a practitioner. This is a discussion firmly aimed at practitioners. Although the Parker (2020) discussion is largely academic, endeavoring to lay a firm theoretical foundation, this discussion is strictly practical. I strive to present, as simply as possible, only the necessary and relevant bits, and to present them in a way that respects the investment of your time and mental energy. I know as well as anyone how precious those final two can be.

AN INTRODUCTION TO THE THEORY

Beginning from simple axioms, Parker (2020) arrives at a model for the allocation of wealth within and across goals. Let us suppose our client names all of her goals. Putting them in order from most important to least important, we will track them as: *A*, *B*, *C* and so on (*A* is most important, *B* is next most important, etc.). From there, we can assume she values them relative to one another, so we assign a value function (this is just an artifact of the math, there is no actual function). Let's call it $v(\cdot)$. We'll call the function representing the probability of goal achievement as $\phi(\cdot)$, and we can see that the client's happiness with our work, dubbed u, is equal to the sum of the goal values we help her to achieve times the probability of achieving them:

$$u = \sum_{i}^{N} v(i)\phi(i). \tag{1}$$

We need some clarity around the $\phi(\cdot)$ function. Thinking about the definition of a goal, we would likely agree that, at a minimum, it is some amount of money needed by some point in the future. For the sake of our definition, we also assume our client has dedicated some initial wealth toward the achievement of that goal. Let's call W the wealth required to achieve the goal, and t the time horizon over which it must be achieved. Because our client has a total pool of wealth to draw from, the initial wealth dedicated to the goal is the goal's allocation (percent of total, let's call it ϑ) times the total value of the wealth pool, represented as ϖ. A goal's achievement probability, then, is some function of these variables. Updating our equation:

$$u = \sum_{i}^{N} v(i)\phi(\vartheta_i\varpi;\ W_i, t_i). \tag{2}$$

Note how $v(i)$ (the goal's value), ϑ (the goal's allocation), W (the goal's funding requirement), and t (the goal's time horizon) are indexed—they are specific to each goal. Our client's philanthropy goal, for example, will have a different priority, time horizon, and funding requirement than her goal to replace business income.

From here, the practitioner must make a choice with respect to the proper modeling of $\phi(\cdot)$. For simplicity and ease of demonstration, we are going to assume statistical normalcy, specifically Gaussian. This is consistent with the theoretical literature, but I recognize it is not indicative of real-world markets. Even so, we press ahead with an understanding that we are engaging in some practical shorthand.

The probability of goal achievement, then, is defined as the upper-tail Gaussian cumulative distribution function, $\phi(\vartheta\varpi, W, t) = 1 - \Phi(\frac{W}{\vartheta\varpi}^{\frac{1}{t}} - 1; m, s)$ where m is the investment portfolio's average return and s is the portfolio's standard deviation of returns. Both of those variables are, of course, determined by the weight dedicated to each investment in the investment universe, dubbed ω.

Putting all of this together, it is obviously our job to make the client as happy as possible—to maximize u. We do that by varying both the allocation across goals and the weights of investments within each goal,

$$\max_{\vartheta,\omega} \sum_{i}^{N} v(i)\phi(\vartheta_i\varpi,\ W_i,\ t_i). \tag{3}$$

And that is pretty much the theory. As I alluded to earlier, there are some practical challenges here, and that is the subject of the next section.

POSSIBLE IMPLEMENTATION

In an effort to illustrate the process, let's consider a case study. For interested readers, I have made the code script and relevant data inputs available at the footnoted link.[2] This case study is obviously highly simplified, but

[2] https://drive.google.com/open?id=1f1nqEyA345dO3FiZ-Jk2oVwA96PKXxtY.

the techniques herein may be imbedded in more complex planning structures. For a detailed analysis and process for those, I invite you to invest some time with Brunel (2015).

Suppose our client presents with the following goal characteristics:

- An estate to their children of $5,000,000, planned for 30 years.
- Living expenses, funded with $5,157,000, needed in 10 years.[3]
- A vacation home, with an estimated funding need of $713,500 in 4 years.
- If possible, the client would like to donate $8,812,000 to their alma mater, planned for 18 years from now. This donation carries naming rights to an athletic building.
- The client has a current wealth pool from which to draw of $4,654,000.

With these details in mind, we can demonstrate the optimization procedure.

Most obviously, no work can begin until the client's goals are understood and funding requirements established. This typically involves ample conversation, financial planning, and psychological forecasting. In the details provided, I have assumed that such conversational work has been done. Though I do not enumerate it, this is very obviously a critical step!

Capital Market Expectations

Before any portfolio optimization can begin, a firm must build its capital market expectations. This is where firms can add significant value—all else being equal, better capital market expectations yield better investment outcomes. It is beyond the scope of this discussion to survey the possible approaches (there are likely as many as there are practitioners). That said, Parker (2017) offers a market-based forecasting model that is integrated into a goals-based approach. For the purposes of this discussion, I assume that the practitioner has an approach, and that the results of the analysis are listed in Exhibit 1. Although I have not included them here (they are in the footnoted link), correlation forecasts are just as important as forecasts of return and volatility.

The Value-of-Goals Function

The first step in our optimization procedure is to determine the relative value of one goal to another. That is to say, how much does our client value funding their living expense versus attaining a vacation home? To ascertain these values, I recommend using certainty equivalent method, though I make no claim it is the most effective way to determine such things. I leave that question to more qualified researchers.

The certainty equivalence is the point at which our client is indifferent to the sure achievement of a less important goal and the probable of achievement of a more important goal. We begin by asking the client to order her goals. We then ask a series of questions (they need not be so sterile; an illustration has its limits): *Would you rather achieve the less important goal with certainty, or the more important goal with probability p?*[4] We adjust the value of p until our client is indifferent to the choice. This, then, is our value-ratio of the two goals.

In the example, our client ranks her goals from most important to least: Living expenses are most important; the children's estate is second; a vacation home purchase is third, and naming rights on a building at her alma mater is last.[5] In the language of behavioral finance,

[3] It may be appropriate to break "living expenses" into two goals of equal priority but of differing time-horizons and funding need. This could better reflect things like lessened travel as the client ages, or perhaps a plan to transition to lower living expenses over the first few years of retirement. Any goal may be broken down like this if the situation necessitates it, though there is a balance to be struck between simplicity and accuracy.

I also acknowledge that not all goals may be stated so precisely. There are numerous examples of fuzzy goals wherein some part (or all) of them is not well defined. In these moments, we must rely on wisdom, experience, and client conversation to find the best way to model them. I would be eager to learn how others approach this common problem!

[4] Note that this is somewhat different from the Brunel (2015) approach, which asks for the maximal probability of failure one would be willing to accept to achieve the goal. The idea here is to ascertain the probability of achievement relative to another goal. It is a "would you rather" question. In that sense, time horizon should not play a role at this stage—the investor can assume that there is a magical wand that can deliver the exact probabilities named over whatever time horizon the goal takes place.

[5] As with any new framework, there are open questions. One that most immediately comes to mind are *nested goals*. That is, some goals must be achieved to achieve others; they are not always mutually exclusive, as I have indicated here. For example, to leave an estate to children we must assume financial survival over the course of retirement. In that respect, the estate goal is nested within the living expenses goal. Exactly how nested goals should be treated is, at the moment, an open question.

EXHIBIT 1
Capital Market Expectations

	Return Forecast	Volatility Forecast
Equity		
Large Cap	0.09	0.15
Mid Cap	0.11	0.16
Small Cap	0.12	0.17
Int'l Developed	0.07	0.15
Emerging Markets	0.09	0.17
Fixed Income		
US Agg Bond	0.04	0.05
US High Yield	0.06	0.09
US Treasury	0.03	0.03
Corporate	0.05	0.07
Alts		
Gold	0.06	0.19
Oil	0.04	0.32
Lottery-Like		
Private Equity	0.15	0.28
Venture Capital	0.16	0.30
Angel Venture	–0.01	0.82
Cash	0.01	0.001

the vacation home is quasi-aspirational; the university contribution is entirely aspirational.

From here, we assign an arbitrary positive number to her most important goal. The value of the living expense goal will be equal to 1, and we can now set about ascertaining the value-ratios of the other goals:

> Would you rather leave your children an estate with certainty, or achieve living expenses with probability *p*?

We vary *p* until she becomes indifferent between the two. Record this value. In our example, the point of her indifference is 0.45. We then work with the client to ascertain the next value-ratio:

> Would you rather purchase the vacation home with certainty, or leave your children an estate with probability *p*?

Again, varying *p* until she cannot decide between the two. Record this value. In our example, the value is 0.50. We continue in this manner until all her goals have been addressed. For the sake of our example, the value ratios are:

- 1.00 for her living expenses goal,
- 0.45 for her estate goal,
- 0.50 for her vacation home, and
- 0.58 for her naming rights goal.

It is important to note that these value-ratios are not the actual *values* of the goals. There is one more step to gain the goal values, $v(\cdot)$, to plug into our model: The value of a goal is the product of value-ratios of the more important goals. So, the value of our client's aspirational building-naming is $1 \times 0.45 \times 0.50 \times 0.58 = 0.13$; her vacation home goal is valued at $1 \times 0.45 \times 0.5 = 0.23$; the value of her children's estate goal is $1 \times 0.45 = 0.45$, and we already declared the value of her most important goal as 1.00. We now have our input for goal values.

Some research into the linkage of common language and goal valuations would be valuable in this step. For example, Brunel (2015, p. 83) suggests a word series "needs, wants, wishes, dreams" to describe the relative importance of goals. Some link between this "linguistic artifice" (to borrow Brunel's phrasing) and the necessity for quantitative input would be valuable, as it appears unlikely to me that clients have the patience to reveal their preferences with the granularity assumed by the model.

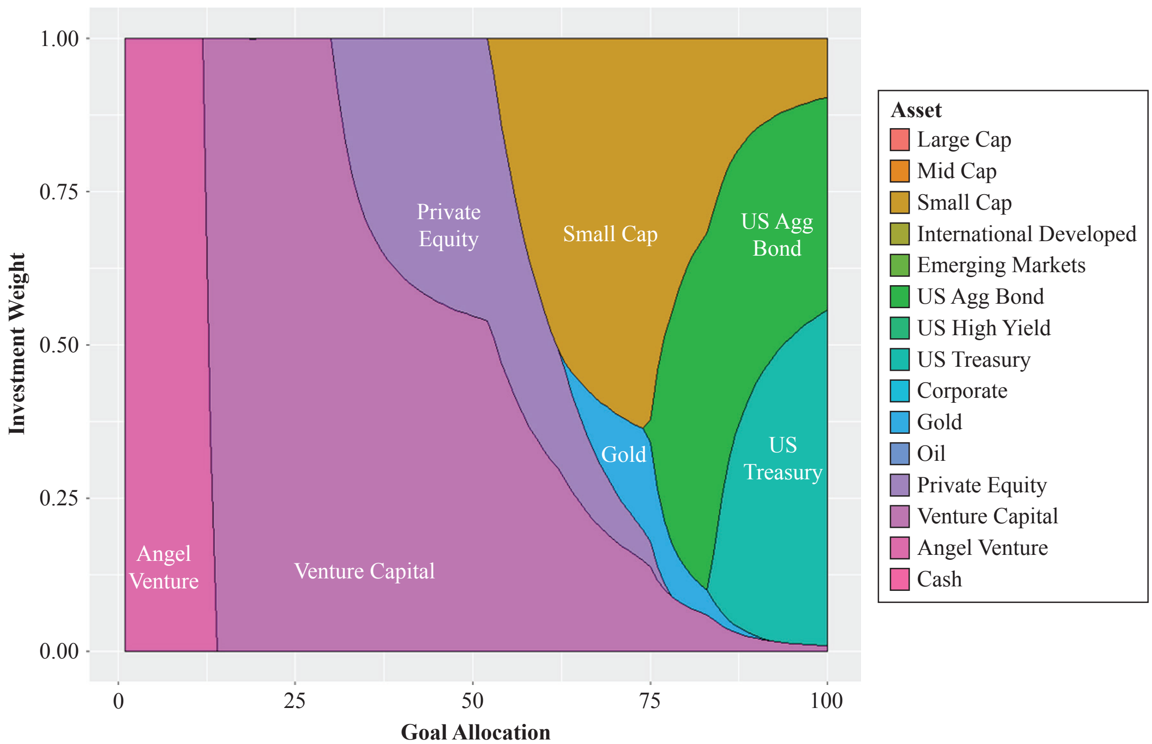
Investment Allocation, Optimization Within Goals

As I mentioned earlier, a major computational challenge is recursion. The optimal allocation of wealth to a goal is, in part, determined by the goal's investment mix. The optimal investment mix, however, is in part determined by the allocation of wealth to the goal. I propose a two-step process for solving this problem. First, we find the optimal mix of investments within each goal for each potential level of wealth allocation to that goal. Next, we feed the potential portfolio returns and volatilities to the algorithm to determine the optimal goal-level allocation.

Using the optimization engine of Ghalanos and Theussl (2015), we find the mix of investments that delivers the maximum probability of goal achievement,

EXHIBIT 2

Investment Allocation as a Function of Goal Allocation



Notes: For the example client's living expenses goal. Note the reliance on the lottery-like Angel Venture asset for low across-goal allocations (1% to 20% range). In mean-variance portfolio theory, low goal-level allocations produce infeasible solutions. In goals-based portfolio theory, low goal-level allocations are feasible and rely on lottery-like assets. As the goal-level allocation increases, the portfolio becomes a traditional stock/bond mix (75% to 100% range) and is synonymous with mean-variance optimization.

given each level of goal allocation (ϑ). In other words, we want to find the best investment mix when 1% of the wealth pool is allocated to the goal, 2%, 3%, and so on. Exhibit 2 illustrates the result of this algorithm for the living expenses goal. We must also record the resultant achievement probability for the best allocation at each level of across-goal allocation.

Goal Allocation, Optimization Across Goals

Armed with an understanding of the within-goal portfolio characteristics for varying levels of goal-level allocations, we now can optimize the goal-level allocation of wealth. Again, practitioners may have a preferred optimization procedure (there are numerous minimax programs in the toolbox), but I demonstrate using a Monte Carlo engine.

First, simulate potential goal weights. Second, plug the simulated combinations into the utility function, drawing the achievement probability from the results of the previous step. Third, return the highest value of utility. Finally, match the across-goal allocation with optimal within-goal portfolio weights (determined in the previous step) and return the optimal within-goal allocations.

Our Example, Finalized

Following this procedure, we find the optimal allocation of the initial pool of wealth, both across goals as well as within them. Exhibit 3 illustrates these results. From Exhibit 3 and the single goal illustration of Exhibit 2, the implications of our approach become clearer. The highly-valued living expense goal receives 81% of the wealth pool, which is enough to generate a 72% probability of success. The children's estate goal receives merely 3% of the wealth pool, but due to the time horizon and available investment universe, it is

EXHIBIT 3

Resultant Allocation of Wealth Both Across and Within Goals

		Goals and their Allocations			
	Aggregate Portfolio	Living Expenses	Children's Estate	Vacation Home	Naming Rights
Goal Allocation		**81%**	**3%**	**15%**	**2%**
Equity					
Large Cap	0%	0%	0%	0%	0%
Mid Cap	0%	0%	0%	0%	0%
Small Cap	29%	36%	0%	0%	0%
Int'l Developed	0%	0%	0%	0%	0%
Emerging Markets	0%	0%	0%	0%	0%
Fixed Income					
US Agg Bond	42%	52%	0%	0%	0%
US High Yield	0%	0%	0%	0%	0%
US Treasury	0%	0%	0%	0%	0%
Corporate	0%	0%	0%	0%	0%
Alts					
Gold	4%	5%	0%	0%	0%
Oil	0%	0%	0%	0%	0%
Lottery-Like					
Private Equity	1%	0%	25%	0%	0%
Venture Capital	7%	7%	75%	0%	0%
Angel Venture	2%	0%	0%	0%	100%
Cash	15%	0%	0%	100%	0%

Notes: This exhibit lists the goal-level allocation, the allocations of the goal subportfolios, as well as the aggregate resultant investment portfolio. For goal-level allocations that are a significant percentage of their funding requirements, the investment allocations are in-line with more traditional allocation frameworks. For subportfolios receiving a goal-level allocation that is not a significant percentage of their funding requirements (and where traditional frameworks cease to return solutions), the allocation leans more heavily on lottery-like assets, as exampled by the naming rights goal. Not all figures sum to 100% due to rounding.

enough to endow it with a 55% probability of success. Note how dependent it becomes on the high-variance, high-return investments of private equity and venture capital. Our client's vacation home goal receives 15% of the wealth pool, generating a 100% probability of success (our allocation engine directs fully funded goals to all cash for safekeeping). Finally, the purely aspirational naming rights goal garners a mere 2% of the wealth pool. True to form, this goal will only be achieved if the lottery-like angel venture investments pay off. Even so, it still commands a 36% probability of achievement.

In a mean-variance paradigm, some of these results would be strictly infeasible. Of more import, however, is the elimination of the lottery-like category from the mean-variance universe. When the expected portfolio return is less than the required portfolio return, probabilities are increased by increasing variance. The minimization of variance, or even the use of variance-aversion as an optimization parameter, is an alien exercise in the goals-based paradigm. Maintaining mean-variance optimization in an otherwise goals-based context will generate lower probabilities of goal achievement, as Parker (2020) showed. Even so, I offer an adaptation to the mean-variance approach that eliminates infeasible solutions in the next section.

GOAL ALLOCATION WITH MEAN-VARIANCE CONSTRAINTS, AN ADAPTATION

Though the probability-maximization component of goals-based utility yields higher goal achievement probability than mean-variance optimization, I realize that, for myriad reasons, many investors are mean-variance constrained. In this section I address how the across-goal allocation component of goals-based utility can be implemented when the within-goal investment allocations are subject to mean-variance constraints.

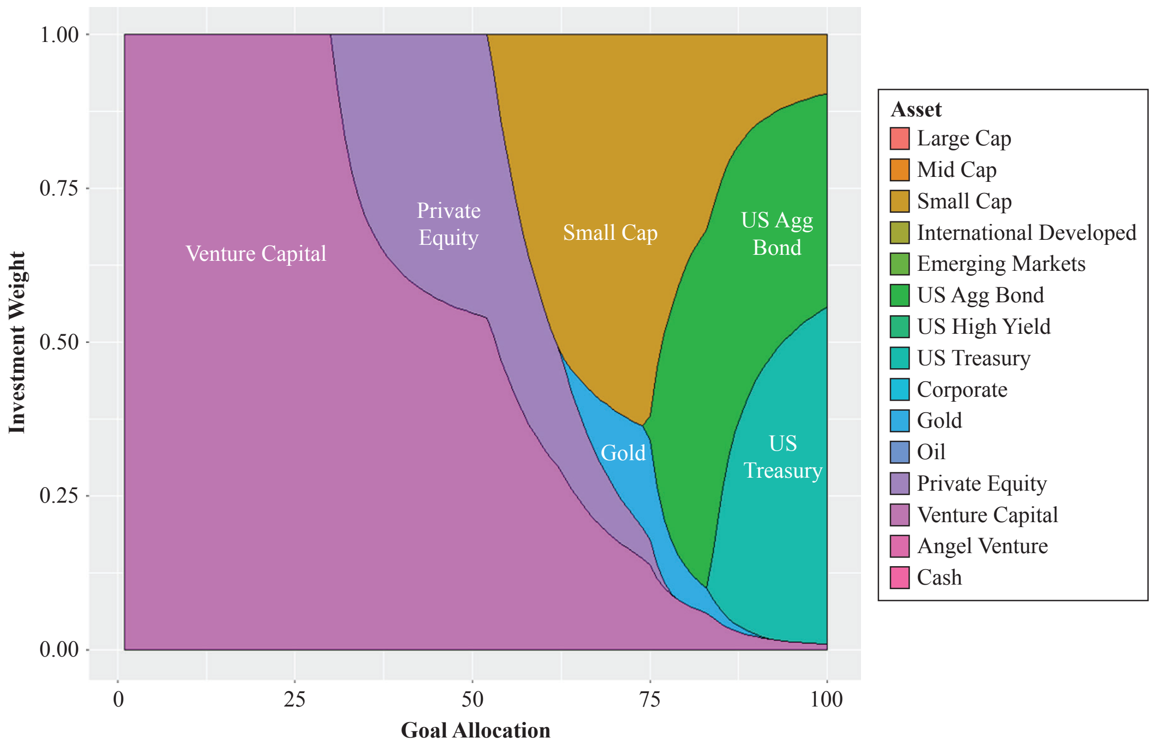
As before, the firm begins by setting capital market expectations then determines the relative values of the client's goals. A mean-variance efficient frontier can be constructed, and each point along the frontier converted into a goal-achievement probability using the expected return and volatility of a portfolio. Because individuals are bounded in their ability to borrow and sell short, there will be some endpoint to the frontier. When the return requirements of a goal exceed the return on offer by the endpoint of the frontier, the portfolio allocation simply maintains an allocation to the last portfolio on the frontier.

From there, the across-goal allocation proceeds as before. After converting the portfolio return and volatility expectations in to goal achievement probabilities, the optimal across-goal allocations can be determined and returned. As mentioned, the code structure to demonstrate this procedure is available in the footnoted link.

Exhibit 4 illustrates the difference in allocation recommendations generated using mean-variance constraints. As becomes clear from Exhibit 4, mean-variance

EXHIBIT 4

Investment Allocation as a Function of Goal Allocation, with Mean-Variance Constraints



Notes: For the client's living expenses goal. Note the elimination of the Angel Venture asset for lower goal-level allocations. The adaptation illustrated here, although still inferior from a goal-achievement perspective, offers feasible solutions where other goals-based frameworks do not.

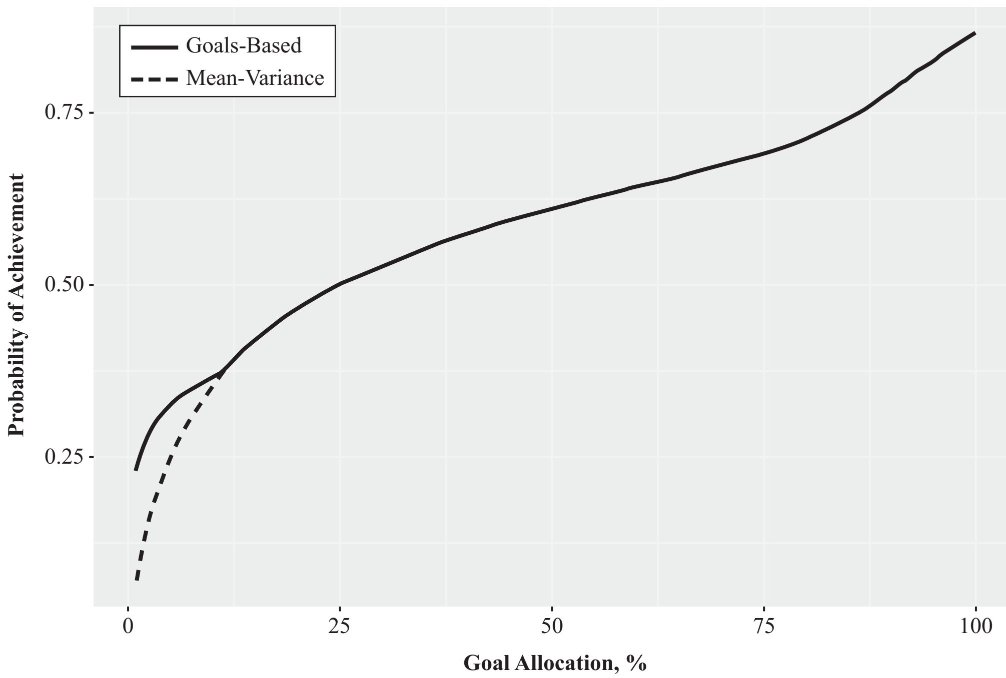
constraints eliminate the high-variance, low return angel venture asset class from the investment universe. This asset class plays an important role in low across-goal allocations for strict goals-based optimization, and thus its elimination lowers the ability of our client to achieve her goals.

In our example, optimizing with mean-variance constraints results in the same across-goal allocation. However, the within-goal allocation shifts for the naming rights goal. Whereas the angel venture asset class captured 100% of the allocation under the strict goals-based optimization procedure, it captures none of the allocation when mean-variance restrictions are applied. Instead, the allocation shifts to 100% venture capital (the endpoint of the frontier). This change is enough to drop the probability of achievement to 34%. To be fair, this is not a huge difference (36% to 34%), but it is enough to demonstrate the point. Given a different investment universe and goal details, the shift in achievement probability may be larger.

Exhibit 5 illustrates the costs of mean-variance restrictions within the living expenses goal. For higher amounts of across-goal allocation, the probability of achievement is equal. However, for lower levels of allocation, the goals-based approach offers considerably higher probabilities of achievement.

All of that said, we should note that this is an adaptation to the strict goals-based procedure, and it does carry benefits. Some of the results we are able to derive with the adaptation are infeasible in other goals-based frameworks, such as Das et al. (2010) and Brunel (2015). The naming rights goal is an illustration of this point. Under previous approaches, it would be declared infeasible and the client would need to adjust some of the goal parameters. Indeed, Elton et al. (2009) explicitly state that the portfolio's required return must be less than its expected return for mean-variance theory to apply. Though it may be tempting to simply constrain-away such goals, it is not reflective of how investors approach

EXHIBIT 5
Mean-Variance Portfolios are Stochastically Dominated by Goals-Based Portfolios



Notes: For higher across-goal allocations, mean-variance portfolios and goals-based portfolios are the same. As the wealth allocation drops, goals-based portfolios begin to deliver more achievement probability than those that are mean-variance constrained. The point of departure between the two is the point at which solutions become infeasible under current goals-based paradigms. This mean-variance adapted form, although inferior to strict goals-based optimization, has the benefit of feasible solutions for investors who are mean-variance constrained.

the investment problem. The GBU framework takes account of all goals—aspirational or not—and provides continuous and feasible solutions across them.

EVOLUTION OF GOALS THROUGH TIME

Goals are not often static. As life progresses, individuals (and institutions) change priorities, respond to unexpected events, abandon goals and add new ones. Any financial architecture must be able to deal with such real-world complexities. Here I discuss (and show through our example) how this model is applied through time and in response to important life events. As I hope to show, the flexibility and responsiveness of the goals-based approach is quite appealing.

Properly speaking, equation (3) is myopic. That is to say, it is reflective of this moment in time only, it is not concerned with the next. In theory, an individual should optimize their intertemporal utility in continuous time, but in reality things are not so simple. For one, any intertemporal optimization is still done with this moment's variables. Today's priorities, goals, and desires are cast forward in time, but are still assumed to be static. Although intertemporal optimization is technically correct, I am not convinced that the extra effort is worth the marginal payoff when we know priorities and goals tend to change and it will all get adjusted anyway.

More than this, in practice it is simple enough to re-evaluate the plan and reoptimize at regular intervals (say, monthly or quarterly). This, of course, is quite familiar, as it is already reflective of most client service models. At every evaluation the procedure remains the same; the inputs are simply updated to reflect whatever new reality the individual may face. The goals and investments are then reoptimized and rebalanced.

There are also real-world frictions that frustrate any effort to adjust through time. This approach may require a rebalance across goals, which is fine in theory, but not so simple when considering the locked-up nature of various account types, such as retirement, education, trusts, and private business. Once capital is dedicated to such accounts, it cannot be easily rebalanced into other goals. This could be overcome through various techniques: by accounting for human capital (if the individual is young) and adjusting future contributions, or (if the individual is sophisticated enough) through the use of more arcane financial instruments. In the end, there is ample room for tradecraft. Advisors must use their judgement, wisdom, and conversational ability to help clients decide the best course when faced with real world situations.

Let us here return to our case study to illustrate the concept. Imagine our hypothetical client took our advice and two years have now passed. A months ago, there was a critical loss in the client's business that requires $352,000 to fix, and it must be dealt with in the coming year. Assuming markets grew in-line with our original capital market expectations, the client has the following financial accounts (with the asset breakdowns listed in Exhibit 3):

- $4,392,954 in the living expenses account,
- $187,063 dedicated to the children's estate,
- $700,000 in a vacation home (approximate value, all of which is equity in the home), and
- $93,080 in the naming rights account.

In addition to account growth, other things have changed, as well. The client now owns their vacation home, so this goal must be restated. Rather than buy a home, the goal is to keep the home with no debt. Our example client is less concerned with maintaining no debt on the home and is willing to maintain a mortgage on it (especially given the circumstances). Also, although the business fix is important, it is just as important to the client as funding their future living expenses. Thus, the value ratio for both goals is 1—they both occupy the top of the hierarchy.[6] Rerunning the goals-based procedure with these updates to the goal-space, pool of wealth, and time horizons, we find that the optimal allocation of wealth to each goal is now

- $352,000 to fix the business,
- $3,985,069 to fund future living expenses,
- $323,113 to the children's estate,
- $592,375 to the vacation home, and
- $107,704 to the naming rights goal.

Our advice, then, is to reallocate $407,000 from the living expenses[7] account and to take $108,000 of equity from the vacation home. This $515,000 is used to fund the business fix and increase the children's estate funding. About $10,000 is also redirected toward the naming rights goal.

In this example, we were somewhat fortunate. Had the model recommended the sale of illiquid funds or the removal of wealth from the children's estate, we may have had to conduct more financial acrobatics.[8] It is in these moments, by the way, where practitioners can add significant value. Goals-based investing is about more than just selecting which investments to own. Often, it is about how you gain or shed exposure to the risks you can or cannot afford to take.

IMPLICATIONS OF THE GOALS-BASED APPROACH

The goals-based approach has a certain practical and obvious nature: People have goals they want to achieve, which is why they sacrifice consumption today; that is why they invest. Thaler's (1985) mental accounting framework was foundational because it proposed that people divvy their savings into mental buckets. Each bucket has a different purpose—some dedicated to daily living expenses, some dedicated to important future consumption (like retirement), and some dedicated to low-probability, life-changing goals (i.e., aspirational goals).

The first major concern with goals-based investing was whether the physical manifestation of the mental accounting structure was an inefficient use of resources. Does divvying assets into different accounts, with each account dedicated to a separate goal, lead to a loss of portfolio efficiency? Brunel (2006) was the first to tackle such a question, delivering a qualified *no*. So long as short-sales and leverage are allowed, Brunel found no significant loss of efficiency in practice. This is an

[6] It may be more technically correct to nest the goal-space as contingent on the business fix. Retirement is, after all, based on the assumption that you have financially survived in previous periods.

[7] For those who are curious, the probability of achieving their living expense goal is 71% after the rebalance.

[8] Or we could ignore the model. We do not always have the luxury of behaving optimally when survival is at stake.

immense relief, because there are numerous real-world frictions that impose a physical manifestation of the mental accounting framework. In many tax jurisdictions, retirement accounts are locked-up, outright preventing account aggregation, to name just one example of these real-world frictions.

Shefrin and Statman (2000) pushed Thaler's idea forward, forming behavioral portfolio theory (BPT). Their fundamental breakthrough was the redefinition of risk. Risk, they assert, is not variance as defined by Markowitz (1952). Rather, they assert that risk is the probability of failing to achieve a goal. It should be the objective to maximize goal achievement probability, not necessarily to reduce variance. A simple idea, but a profound insight contrary to standard economic thought.

Though the implementation of BPT never gained mainstream acceptance, there was concern that such a redefinition of risk would lead to absurd results. That is until Das et al. (2010) proved that, so long as short-sales and leverage were allowed, BPT and mean-variance theory were synonymous for most cases. They also echoed Brunel's (2006) result that the mental accounting structure is not necessarily inefficient. Their work had the ultimate effect of reinforcing the mean-variance approach in goals-based settings.

From there, Brunel (2011, 2015) constructed a practical system, consolidating this (and other) disparate work into a whole—a practical application of the theory to help people in the real-world achieve their financial goals more often.

Brunel (2020) discussed the now not-so-clear line between financial planner and investment manager. Our discussion here, and the results contained in Parker (2020), confirm his thesis. Although a mean-variance paradigm makes it easier to separate the roles, the goals-based framework makes that separation much less justifiable. The two are inextricably linked in the goals-based framework, with goals determining the investments and the investments, in turn, determining the allocation across goals. This level of integration is not conducive to outsourcing, and, thus, the standard industry approach may need upending.

Currently, firms build model portfolios that approximate client needs—low to high risk, low to high liquidity, low to high tax consideration, and so on. With the advent of more automated systems and the proliferation of inexpensive computing power, firms now have the ability to deliver highly individualized solutions. Rather than attempt to fit client needs to the approximations of model portfolios, firms can now build fully customized solutions. These solutions can incorporate the firm's investment view, the client's ethical constraints, the client's specific goal constraints (liquidity, time horizon, return need, etc.), as well as any other relevant specifics. I believe this is how we, as an industry, may hold-off the dreaded *feepocalypse* that has long been foretold. The approach I present here, as well as the fuller theory of Parker (2020), are a critical key to the automation of such solutions.

Such a shifting structure will, of course, require adaptation. Org charts will need updating, yes, but so will skill-sets. System-building and coding, with substantial oversight and critical analysis, will be key components in such a future. Although face-to-face conversation will undoubtedly continue in its critical role, the actual behind-the-scenes execution of investments, plans, and client servicing will likely come to more resemble a technology company than a traditional wealth management firm. Changing demographics will contribute to this trend as millennials—who stand to benefit from the largest wealth transfer in the history of mankind—will demand the now-familiar digital tools and techniques on which they have come to rely.

No changes in the financial universe are complete without changes in regulation. How regulators oversee a world of algorithmic trading, proliferated across the whole ecosystem of financial services, is a question yet to be answered. In-house compliance teams will require new and different tools to ensure algorithms behave as advertised, coders aren't burying millisecond frauds in millions of lines of code, and ethical standards are maintained. Many academic breakthroughs are probably required to ensure effective and efficient oversight. We may shortly enter an age where Nobel laureates in economics are computer scientists by trade. This leads to yet even bigger questions: What will regulators deem acceptable in this rapidly changing world of algorithms? Are they even currently qualified to know? Are we?

In this vein, the goals-based framework makes the use of risk tolerance questionnaires highly dubious. Pan and Statman (2012) questioned their use on the grounds that they are ineffective. The goals-based framework makes them entirely superfluous. Basing investment decisions on a risk tolerance questionnaire is like a medical doctor basing treatment on a pain tolerance questionnaire. It might be relevant, but it is hardly the final word. Of course, risk tolerance questionnaires began as a way to ascertain an individual's risk aversion parameter—a critical input to the quadratic utility form of mean-variance theory. The abandonment of mean-variance theory should mean the abandonment of risk tolerance questionnaires, but their use will probably remain due to regulatory ossification.

Another unfamiliar outcome of the goals-based framework is the use of lottery-like assets. High-variance investments have been generally shunned by the public, but more harshly so by regulators. Reg D rules,[9] for example, are a salient example of regulators' unwillingness to allow wider use of lottery-like assets. Of course, Thaler (1985) and Statman (2004), among others, proposed that individuals would pursue aspirational goals. What are aspirational goals if not those that are unattainable by the traditional investment space? For goals-based practitioners (and their clients), the use of high-variance investments is a decidedly rational way to achieve goals, as Parker (2020) showed. I should mention, however, that it certainly is not rational to gamble everything, or even to gamble with high-value goals. In this respect, the work of Parker (2020) acts as an important curb to the pursuit of aspirational goals. Whereas behavioral finance admits aspirational goals but offers no *shoulds* with respect to them, and traditional finance simply constrains them away,[10] the goals-based framework both acknowledges their existence and defines a budget for them.

This aspect of the theory raises a new and intriguing question. What is prudent in the realm of high-variance, low-return investing? Obviously, there is some marginal rate of substitution for volatility and return; that is, high volatility is not the only factor in play, return matters, too. Practitioners will need to grapple with this question of prudence if they are to deploy client capital into lottery-like investments.

When viewed in light of the other theoretical frameworks present in the literature, the practicality of the goals-based framework becomes more evident. First, goals-based solutions are feasible where mean-variance solutions are infeasible. This is due to the allowance of high-variance outcomes and the removal of the expected-return-must-be-greater-than-required-return constraint. Second, whereas previous goals-based solutions can allocate part of the wealth pool, the Parker (2020) model allocates the entirety of the wealth pool. Third, we have gained a better understanding of how one might effectively substitute one goal for another. Given multiple competing goals over varying time horizons, we can now answer whether a shorter-dated goal may be funded with an acceptable loss of achievement probability for the longer-dated goal. Fourth, and this should be the most important consideration, the probability maximization component of the goals-based framework yields higher probabilities of goal achievement than mean-variance solutions. In technical parlance, goals-based solutions stochastically dominate mean-variance solutions.

Goals-based utility is a two-level allocation problem. At the overarching level, wealth is allocated across goals. Within goals, wealth is allocated across investments. Practitioners may accept the across-goal allocation while simultaneously rejecting the within-goal allocation. I have endeavored to demonstrate how the practitioner may maintain mean-variance efficiency within goals while efficiently allocating across goals. This adaptation has its drawbacks, however, most notably that investors will not reap the highest probabilities of goal achievement. Although I recognize the time-tested appeal of mean-variance theory, I am not sure that orthodoxy alone is enough to justify the use of a provably inferior approach.

As practitioners, we have a solemn ethical duty to our clients. No matter how effective a new approach may appear to be, I must admit that a significant part of our ethical duty is extensive due diligence prior to the implementation of a new framework. I advocate, quite simply, for the initiation of that due diligence. There is much work still to do. There are many unanswered questions. I would expect no less of a new theory. If, however, the goals-based framework does help clients achieve their goals more often than other frameworks, then it becomes our ethical duty to implement the superior approach.

REFERENCES

Brunel, J. 2006. "How Sub-Optimal—If at All—Is Goal-Based Asset Allocation?" *Journal of Wealth Management* 9 (4): 19–34.

[9] For those unfamiliar, a brief definition of the SEC's Regulation D may be found here: https://www.sec.gov/fast-answers/answers-regdhtm.html.

[10] For example, Elton et al. (2009) call for the required portfolio return to be less than the expected portfolio return.

——. 2011. "Goal-Based Wealth Management in Practice." *Journal of Wealth Management* 14 (3): 17–26.

——. 2015. *Goals-Based Wealth Management*. Hoboken, NJ: Wiley and Sons.

——. 2020. "A More Detailed Look at Goals-Based Planning." *Journal of Wealth Management* 22 (4): 21–36.

Das, S., H. Markowitz, J. Schied, and M. Statman. 2010. "Portfolio Optimization with Mental Accounts." *Journal of Financial and Quantitative Analysis* 45 (2): 311–334.

Elton, E., M. Gruber, S. Brown, and W. Goetzmann. 2009. *Modern Portfolio Theory and Investment Analysis*. Hoboken, NJ: John Wiley & Sons.

Ghalanos, A., and S. Theussl. 2015. *Rsolnp: General Nonlinear Optimization Using Augmented Lagrange Multiplier Method*. R Package version 1.16.

Markowitz, H. 1952. "Portfolio Selection." *The Journal of Finance* 7 (1): 77–91.

Pan, C., and M. Statman. 2012. "Questionnaires of Risk Tolerance, Regret, Overconfidence, and Other Investor Propensities." *SCU Leavey School of Business Research Paper No. 10-05* (March 2012).

Parker, F. 2017. "Achieve Your Goals More Often: A Case for Active Allocation." *IFTA Journal*, 2018 ed. pp. 100–106.

——. 2020. "A Goals-Based Theory of Utility." *Journal of Behavioral Finance*. DOI: 10.1080/15427560.2020.1716359.

Shefrin, H., and M. Statman. 2000. "Behavioral Portfolio Theory." *Journal of Financial and Quantitative Analysis* 35 (2): 127–151.

Statman, M. 2004. "The Diversification Puzzle." *Financial Analysts Journal* 60 (4): 44–53.

Thaler, R. 1985. "Mental Accounting and Consumer Choice." *Marketing Science* 4 (3): 199–214.

ADDITIONAL READING

How Sub-Optimal—If at All—Is Goal-Based Asset Allocation?
Jean L.P. Brunel
The Journal of Wealth Management
https://jwm.pm-research.com/content/9/2/19

ABSTRACT: *Following the success enjoyed by goal-based allocation over the last several years, the author investigates what the focus away from traditional finance and toward behavioral finance may be costing, if anything, in terms of traditional investment efficiency. The author starts with a review of the modern portfolio theory framework and offers a hypothesis as to how the demonstrated inability of individuals to stick to a single optimal portfolio might be interpreted. He then goes on to review the behavioral solution of a hypothetical case study and compares the outcome with a traditional optimization. His analysis suggests that, once goal-based allocation is re-formulated to allow some focus on the total portfolio trade-off between risk and return, the cost in terms of theoretical sub-optimality may be viewed as trivial. He does however concede that this experiment is unlikely to close the debate between the two branches of finance, as the analysis allows each side to claim some form of victory.*

Goal-Based Wealth Management in Practice
Jean L.P. Brunel
The Journal of Wealth Management
https://jwm.pm-research.com/content/14/3/17

ABSTRACT: *Though goals-based wealth management is certainly not a radically new discipline, it has recently assumed a more important role within the private wealth management industry. Two discrete factors probably stand behind this development: a change in client perceptions of risk after the 2008 market melt-down and the publication of the seminal piece by Das, Markowitz, Scheid, and Statman. This article starts with a review of the key issues which families typically face when dealing with wealth planning, then discusses a framework which allows advisors to consider financial, estate, and investment-planning needs, shows the practical considerations associated with the process and concludes with a brief discussion of the major business challenges that still need to be addressed.*

Extending the Goals-Based Framework to Comprise Both Investment and Financial Planning
Jean L.P. Brunel
The Journal of Wealth Management
https://jwm.pm-research.com/content/22/4/21

ABSTRACT: *This article seeks to fill a void in the literature on goals-based planning. Most of the current work covers cases where clients already possess significant financial assets that they plan on* *totally or partially spending down, through expenses as well as various dynastic or philanthropic transfers. Yet, planners—be they focused on income/savings/expense management issues or conduct their work in the asset management sphere—have to deal with at least two other potential cases. Our analysis suggests that the goals-based planning approach has the potential to inject more texture into conversations with all clients. It also shows that there are significant, and at times even dramatic, differences in the ways one might deal with (1) an individual who is already wealthy and spending down his or her wealth, (2) another who may be wealthy but has unrealized non-financial wealth and ongoing current savings inflows, and (3) yet another who has a significant income and savings power but not enough accumulated financial wealth to live on. This is nothing more than the classical case of the difference between human and financial capital. Individuals in an asset decumulation mode have more financial than human capital, while those who are in an accumulation mode have more human than financial capital. As one might expect, this describes a full spectrum, and our "accumulation/decumulation case" falls somewhere between these extremes.*