

Asset Allocation in Alternative Investments



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ABSTRACT

Adding direct and fund investments to one's portfolio has the potential to augment risk-adjusted returns, unlock the illiquidity premium, and create targeted portfolio exposure by investment strategy, asset class, portfolio manager, industry sector, geography and liquidity needs. Such investments may facilitate individual investor's access to managers who create skill based returns from security selection and market timing decisions in unique investment structures.

Incorporating such investments into a portfolio, however, requires that investors have the tools to compare these investments in a like-for-like fashion with traditional asset classes. At the strategic level, investors need to account for pricing distortions, inability to rebalance, and other biases in reported data. At the manager level, investors must explicitly be able to differentiate returns that come from a manager's skills and returns that come from simply taking on market risk. Finally, investors should make these decisions in an integrated fashion to ensure that their choices are consistent with their risk and return preferences.

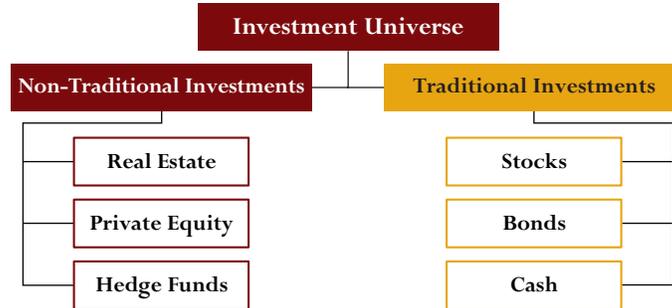
Direct investments have played a valuable role in investor portfolios over the years, from being an important driver of excess returns, to a niche risk diversifier for traditional fixed income and public equity, to a series of interesting, one-off opportunistic trades. We believe that only by accounting for the issues described earlier can investors reliably understand the role direct investments should play in their portfolio. The potential reward for doing so is large. It is therefore critical for the industry to develop, and for investors to adopt, a new framework for asset allocation for direct investing that goes beyond the more traditional mean variance investment analysis.

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INTRODUCTION

The alternative investment (AI) universe consists of investments outside of publicly traded debt, equity, and real estate. It includes investments ranging from hedge funds and managed futures to venture capital, private placements, private equity LBO funds, natural resource partnerships, private real estate and commodity investments.

► Exhibit 1 | Stylized Depiction of Traditional and Non-Traditional Investing Landscape



AI funds are generally not required to register under the Investment Company Act of 1940 and restrictions are placed on investors eligible to access them. They are not listed on an exchange and are offered as private investment funds. AI in general tends to have an absolute performance objective. As such, they do not merely seek to outperform a benchmark, but rather aspire to produce positive returns under varying market conditions. They tend to use leverage¹ to increase returns and their performance is largely dependent on investing skill rather than just market exposure. They have historically exhibited moderate correlation with traditional financial market indices over long periods of time. They typically also exhibit reduced liquidity relative to traditional investments, with monthly to multi-year lock-ups. Their managers typically charge higher fees, which may include performance fees. Historically, adding AI to traditional portfolios has often resulted in enhanced risk-adjusted returns. A feature that is common across most AI categories is the large dispersion of performance across managers. Therefore, even more so than for traditional investments, manager selection is of critical importance in portfolio construction.

As market events are reflected differently in each strategy and in each broad AI category, combining a portfolio of such investments with different but complementary investment styles and risk/return attributes is desirable. However, a naive diversification across a large number of strategies may be suboptimal too. In AI, the process of due

¹ While leverage presents opportunities for increasing the total return on investments, it has the effect of potentially increasing losses as well. Accordingly, the impact of any event which adversely affects the value of an investment could be magnified to the extent leverage is utilized and may result in a substantial loss. This involves borrowing money to increase the effective size of the portfolio, or purchasing securities on margin, or synthetically gaining exposure through futures or options contracts. For traditional mutual funds, leverage is generally not allowed or is limited. But hedge fund returns often rely heavily on leverage.

diligence is typically more time-consuming and costlier than in traditional investments. The reasons include the complexity of holdings and exposures, their diversity, and their lack of transparency. It is therefore important to choose carefully among selected strategies and amongst the managers that practice those strategies. One must also take care to skillfully combine them into robust portfolios. The construction of a portfolio of different AI strategies is a complex task requiring a deep understanding of the statistics commonly used in the financial industry as well as sound investing judgment.

Markowitz’s Classic Mean-Variance Approach. Asset allocation with traditional investments has been well-studied and has become a developed discipline over the last five decades. Markowitz’s classic mean-variance approach is widely used for asset allocation for traditional assets and many asset allocation tools and models have been built around this framework, all of them predicated on a set of implicit assumptions. For example, it is assumed that returns in each asset class can be accurately measured. On the basis of these observations, one can appropriately characterize the risk inherent in each asset class. Similarly, these models rely on the assumption that the asset returns are comparable: for example, that the liquidity in each asset class is roughly comparable. Furthermore, many models rely on an assumption that markets are open to all investors and that these markets operate efficiently, so that information about particular markets is priced in immediately. Finally, many of these models rely on the assumption that risk is appropriately characterized by volatility. Each of these assumptions, while implicit, has been a reasonable approximation of reality when investors and managers study allocations among traditional investments such as cash, fixed income and equities.

However, the increasing use of AI has fundamentally challenged these assumptions. This is because investing in AI is very different from investing in traditional investments.

► **Exhibit 2 | Alternative Asset Classes Differ from Traditional Investments**

Traditional Investments		Alternative Investments
■ Relative Performance Objective	➔	■ Absolute Performance Objective
■ Generally No Leverage	➔	■ May Use Leverage
■ Performance Dependent Primarily on Market Returns	➔	■ Performance Dependent Primarily on Advisor Skill
■ Historically High Correlation with Market Indices	➔	■ Historically Low to Moderate Correlation with Market Indices
■ Typically Offers Daily Liquidity	➔	■ Typically have Reduced Liquidity Ranging from Monthly to 12+ Year Lock-Ups
■ Fixed Management Fee on Assets Under Management	➔	■ Generally Higher Fees Which May Include Performance Fees

■ When it comes to asset allocation using mean-variance optimization, every AI portfolio constructed is likely to be suboptimal. Traditional approaches do not capture AI's asset characteristics—fat tails, asymmetric return distributions, autocorrelation, volatility clustering or mean reversion in time series.

■ Historically, high net worth individuals have been significant investors in AI. In recent years, the mass affluent have been a growing presence.

AI is Different – Markowitz's Classic Mean-Variance Approach Does Not Work.

In illiquid private equity or private real estate for instance, it is very difficult to accurately assess returns on a basis comparable with returns of traditional asset classes. Unlike traditional investments, in which prices are observable on a continuous basis, it is not possible to observe market prices for many hedge fund strategies. This makes it difficult to estimate what a marked-to-market return would be and makes the measurement of risk and, most important, the comparison between various investment risks, extremely difficult. Similarly, the fact that AI usually contain significant restrictions on tradability, unlike their traditional counterparts, implies additional constraints to investors that cannot be accounted for in the standard mean variance framework. Furthermore, unlike traditional investments, AI rely on the notion of restricted markets that exploit inefficiencies. Finally, in many AI, returns are not well approximated by the standard assumption that historical returns are distributed according to a normal, bell-shaped distribution. Thus, the use of volatility as a way of measuring risk will leave investors with potentially unaccounted-for downside risk.

Acknowledging the special returns distributional properties of AI strategies is essential to investing in the asset class. In particular, hedge fund returns are non-normally distributed and exhibit negative skewness² and positive excess kurtosis.³ Some strategies such as credit and distressed securities have the highest degree of non-normality. For instance, credit risk distributions are generally exposed to significant downside risk. This risk is embodied in the form of credit events such as downgrades, defaults, and bankruptcies—the return distribution for high-yield debt is distinctly non-normal and has a negative skew value. This indicates that the distribution of returns associated with credit-risky high yield debt assets have larger negative returns than they do large positive returns; there is a bias to the downside. In addition, they have a positive value of kurtosis. This indicates that credit risk assets are exposed to large negative outlier events.

How do investors deal with challenges of incorporating AI in their portfolios?

This paper attempts to answer this question and provides guidance for making optimal asset allocation and portfolio construction decisions in allocating to private equity, private real estate and hedge funds or alternative mutual funds. It explains the unique challenges in asset allocation to AI and proposes an approach that goes

2 Skewness is a statistical measure to capture asymmetry in the return distribution of an asset. If a time series of an asset has a negative skewness, this might indicate that there is an increased probability of negative returns, compared to a normally distributed time series. In other words, the historical pattern of returns does not resemble a normal (*i.e.*, bell-curve) distribution.

3 Kurtosis is measured relative to a normal, bell-shaped distribution. A positive value for kurtosis indicates a fatter distribution with greater dispersion around the mean with "fatter" than normal tails. It implies a higher probability of extreme outcomes (or large surprises) than would be expected for a normal distribution.

beyond Modern Portfolio Theory (MPT). It also describes ways to address portfolio construction and active management issues that are unique to illiquid private equity/real estate as well as more liquid hedge fund strategies.

CHALLENGES IN ASSET ALLOCATION WITHIN AI

In the traditional asset allocation framework investors seeking greater returns are expected to assume additional risk. Mean variance analysis is a tool of traditional portfolio selection that constructs a portfolio of securities by focusing on the resulting mean expected return and the expected variance of the portfolio. Portfolios are represented in a mean-variance plane. The efficient frontier line represents the set of portfolios with the highest expected return for each given risk level (or lowest risk for each given return level). Those portfolios are called “efficient” portfolios.

This approach however makes a number of simplifying assumptions:

- Returns and risks are measured comparably across asset classes.
- Returns and risks are measured accurately across asset classes.
- Investors have perfect information.
- Liquidity in each asset class is roughly the same.
- Markets are efficient and new information is priced immediately.
- Volatility accurately reflects risk and investors are only concerned about the variance of their returns.
- All investors have the same holding period for their underlying investments.
- All investors can borrow or lend an unlimited amount at the risk-free rate of interest and there are no restrictions on short sales⁴ of any asset.
- All assets are marketable, and there are no transactions costs.
- There are no taxes.

Collectively, these assumptions present a radical departure from the real world; something even more exacerbated when allocating to AI.

⁴ During “short” selling the fund manager borrows securities that it does not own (and pays fees and interest rate charges for such borrowing). The manager then sells such securities with the goal of acquiring them later at a lower price. The manager then returns the borrowed securities and retains the gain (should security prices decline in value), if any, from selling the securities short. If the prices of the borrowed securities rise the manager loses money as those securities need to be bought back at a higher price (for they were borrowed in the first place). To buy and hold something is referred to as taking “long” exposure. they were borrowed in the first place). To buy and hold something is referred to as taking “long” exposure.

■ Data challenges include measuring and forecasting true risk, incorporating the effect of illiquidity, tradability restrictions, reporting bias and information asymmetry, serial correlation, strategy drift, unique risks and other issues posed by active management.

► **Exhibit 3 | Including Alternative Investments in Asset Allocation is a Challenge**

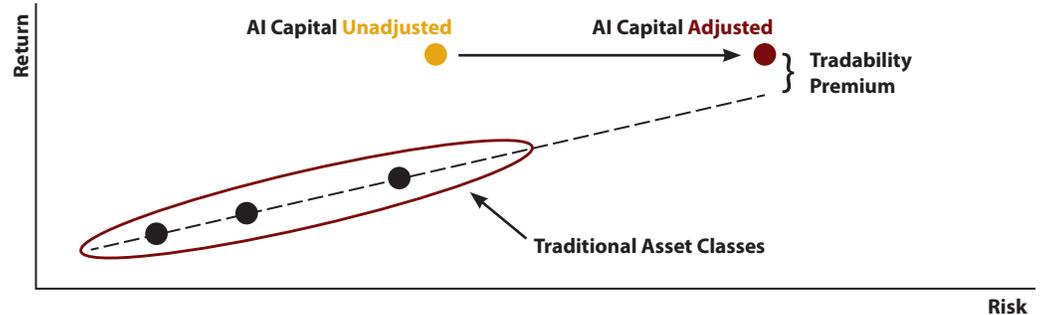
Traditional Investments		Alternative Investments
■ Accurate Measure of Returns	→	■ Inconsistent Measure of Returns
■ Risk is Appropriately Measured	→	■ Risk is Not Captured by Data
■ Asset Returns are Comparable – <i>Marked-To-Market Valuations</i> – <i>All Assets are Fully Liquid</i>	→	■ Asset Returns are Not Comparable – <i>Mixture of Stale and Current Valuations</i> – <i>Variable Degrees of Liquidity</i>
■ Markets Are: – <i>Open to Common Set of Investors</i> – <i>Efficient</i>	→	■ Markets Are: – <i>Not Open to All Investors</i> – <i>Not Efficient</i>
■ Data Measured Over Same Time Period	→	■ Data Measured Over Different Time Periods

Returns and Risks Are Not Measured Comparably and Accurately in Alternative Asset Classes. Unlike traditional investments, in which market prices are observable on a virtually continuous basis, it is not possible to observe market prices for many AI such as private equity or private real estate. This makes it difficult to compare risk/return profiles.

Quality of Information Regarding Different Investment Choices is Often Not Comparable. While broadly diversified traditional asset class performance has been tracked for decades, historical performance data for many AI strategies is much less robust. Further, even in cases where data is available, the evolving nature of these strategies means that, even more than is generally the case, past performance may be a particularly poor input for formulating views on future performance. It is therefore difficult to be as confident in attempting to predict the future performance of AI relative to traditional asset classes.

Liquidity in Each Asset Class is Not Same. Many AI strategies contain significant tradability restrictions – within private equity, investors may have their principal ‘locked up’ for anywhere up to twelve years.

► **Exhibit 4 | Tradability Restrictions Have Implicit Costs**



In other words, there is an implicit option value in being able to trade an asset, a value that is lost for those investing in illiquid strategies. We call this margin the “tradability

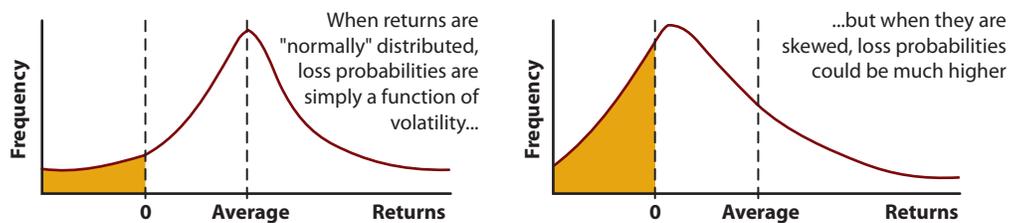
■ AI have unique return drivers and characteristics that differ from traditional investments. In most cases, the primary source of returns is from manager skill and security selection, rather than from pure directional asset class exposure.

premium” that investors should and do collect in exchange for locking up their money. The existence of this premium, to compensate investors for the costs of portfolio drift and for sacrificing the option to meet unforeseen cash flow needs, raises an important issue from the standpoint of classic portfolio construction: namely, traditional portfolio construction occurs in two dimensions: risk and return. This is sensible if returns are generated to compensate for volatility of asset returns. But, when illiquid real estate assets are included in a portfolio, we encounter the fact that they are not necessarily compensating for risk, but for something else: lack of tradability. If we simply leave this tradability premium in a classic model, illiquid assets will garner very high allocations, because, on a risk-adjusted basis, these assets appear to be potentially much more attractive.

Inefficient Markets. Unlike traditional investment managers, AI managers may seek out restricted markets so that they can identify and exploit inefficiencies. These less-efficient markets often have additional forms of risk (e.g., funding risk) that need to be accounted for.

Volatility Does Not Accurately Reflect Risk. Returns for many AI strategies are not distributed symmetrically (normally) around their mean. For this reason, the use of volatility to measure risk is insufficient. Most investors are concerned about other form of downside risks in addition to volatility. The typical volatility measure-standard deviation-may drastically understate the downside risk inherent in many alternative investment strategies.

► **Exhibit 5 | Alternative Investments Historical Returns are Non Normal**



Investing in AI is not without risks and investors need to be aware of important risks. AI have non-normal distributional return properties. AI trading techniques include employing optimal leverage, short selling, hedging and arbitraging mispricing.

Practitioners use ‘Downside Risk’ to express either the likelihood of a loss, or the magnitude of a loss or some measure of the dispersion (risk) of losses that may arise from investing in alternatives. Additionally, several risk adjusted performance ratios that incorporate downside risk have been developed over the past few years. Commonalities in the way to measure and interpret downside risk enable classification of different downside metrics into:

- **(i) Probability of Loss Metrics:** this class of downside risk metrics tries to capture the likelihood of a loss, without any consideration with regards to the size of the loss.
- **(ii) Loss Metrics:** these metrics aim at capturing the magnitude of losses using Value at Risk, Modified VAR, Expected Shortfall or Conditional Value at Risk, Maximum Drawdown etc.

- **(iii) Tail Risk Metrics:** this class of downside risk metrics captures the dispersion in returns below a threshold or minimum acceptable return.
- **(iv) Downside Risk Performance Ratio Metrics:** Investors are often interested in the amount of risk they have, or how much they may stand to lose, but also in whether they are adequately compensated for bearing it. This interest led to the development of risk adjusted performance ratios, of which the Sharpe Ratio⁵ has become the standard in the investment industry. However, the Sharpe ratio is a function of the volatility and thus suffers from the same weaknesses as the volatility itself when applied to non-normal distributions of hedge fund and private equity returns.

Given this gap between the classical assumptions underlying standard asset allocation approaches and the complexities that AI present, investors are left with a dilemma. While many do believe that AI can and does add value to a portfolio, they are often unable to make allocations to alternatives. Models, processes and tools are just not commonly available that provide a systematic evaluation of the risk/return characteristics for AI. In order to solve this dilemma a new approach to portfolio allocation is required. What should this approach be? The cornerstone of this new approach, we submit, may be a reframing of the traditional strategic asset allocation problem beyond binary risk-return tradeoffs to newer types of tradeoffs.

► **Exhibit 6 | Traditional and Direct Investments Have Different Characteristics**

New Asset Classes	Assumptions	
	Traditional Investments	Direct Investments
<ul style="list-style-type: none"> ■ Liquid Hedge Funds ■ Illiquid Non-Traded REITs ■ Illiquid Fixed Income ■ Liquid Managed Futures ■ Illiquid Private Equity 	<ul style="list-style-type: none"> ■ Data accurately measures returns 	<ul style="list-style-type: none"> ■ Inconsistent measurement of returns
	<ul style="list-style-type: none"> ■ Risk is appropriately measured using volatility 	<ul style="list-style-type: none"> ■ Risk not captured by data
	<ul style="list-style-type: none"> ■ Asset returns are comparable <ul style="list-style-type: none"> – <i>Marked-to-market valuations</i> – <i>All assets are fully liquid</i> 	<ul style="list-style-type: none"> ■ Asset returns are not comparable <ul style="list-style-type: none"> – <i>Mixture of stale and current valuations</i> – <i>Variable degrees of liquidity</i>
	<ul style="list-style-type: none"> ■ Markets Are: <ul style="list-style-type: none"> – <i>Open to common set of investors</i> – <i>Efficient</i> 	<ul style="list-style-type: none"> ■ Markets Are: <ul style="list-style-type: none"> – <i>Not open to all investors</i> – <i>Not efficient</i>
	<ul style="list-style-type: none"> ■ Data measured over same time periods 	<ul style="list-style-type: none"> ■ Volatility may not be appropriate risk metric
		<ul style="list-style-type: none"> ■ Data measured over different time periods

⁵ The Sharpe Ratio is the average return, less the risk-free return, divided by the standard deviation of return. The ratio measures the relationship of reward to risk in an investment strategy. When returns are normally distributed as in a bell curve (traditional) the higher the ratio the safer the strategy.

A NEW ASSET ALLOCATION APPROACH

Despite the variety and complexity of investment options, however, there are only a few basic drivers of return. We categorize these drivers into:

Fundamentals. A primary way in which investors seek to make money is by investing in fundamentals—what is often referred to as ‘beta’.⁶ These are investments in the fundamental characteristics of the economy. Economic growth, credit cycles and public debt- each of which drives more proximate performance metrics such as corporate earnings and interest rates- are some examples of fundamental factors. In practice, when investors invest in fundamentals, they determine exposures to traditional asset classes such as equity and fixed-income markets which are driven by fundamental factors.

Skill. A second driver of investment returns is the skill of an investment manager to add value to fundamental investments. This added value is commonly referred to as ‘alpha’.⁷ Many investors decide on a mix of internal and skilled external⁸ managers to allocate their client capital to. External active managers seek to generate alpha in a number of ways: through security selection by buying undervalued securities and selling overvalued ones; through tactical investing by attempting to time entry and exit in various markets; or through control value added by actively intervening in firm governance, financial structure, strategy and/or operations.

Liquidity. When investors purchase assets that do not trade, they give up an option to trade out of these investments. Investors expect to be compensated for ‘selling’ this option. In other words, they expect to obtain an illiquidity premium. AI typically exhibit reduced liquidity relative to traditional investments, with monthly to multi-year lock-ups. Generally, there are no liquidity provisions, no mechanisms in place to sell partial interests in non-realized funds, along with significant restrictions on transfer. Hedge funds sometimes invest in securities, bank debt and other claims which are subject to legal or other restrictions on transfer, or for which no liquid market exists. The market prices for such investments tend to be volatile and may not be readily ascertainable. Hedge fund managers run the risk that they may not be able to sell these securities when they desire to do so or to realize, what they perceive to be their

■ AI is about active management and skill based investing.

⁶ Beta is a measure of the volatility of the security’s return performance relative to a benchmark financial instrument usually a broad index that serves as a proxy for the market. Typically a value of greater than 1 implies that the security is more volatile than the benchmark and a value less than 1 implies less volatility relative to the benchmark.

⁷ A mathematical value indicating an investment’s excess return relative to a benchmark. Alpha measures a manager’s value added relative to a passive strategy, independent of the market movement.

⁸ Criteria for choosing external managers usually includes assessing; (i) competence / fundamental and technical expertise (ii) resources and capabilities availability and dedication (iii) track record of risk management and performance (iv) investment philosophy (v) complexity of investment strategy (vi) assets under management and number of public sector / central banks clients (vii) costs (viii) control issues.

fair value in the event of a sale. Also, the sale of restricted and illiquid securities often requires more time and results in higher brokerage charges or dealer discounts and other selling expenses, than does the sale of securities eligible for trading on national securities exchanges, or in the over-the-counter markets. If investors, who do not require immediate liquidity for their investments, are able to hold on to these investments they often have the potential to receive handsome returns. In another case, a complex security that may have very narrow markets may trade at lower prices which reflects lack of liquidity; a security's bid/ask spread may offer insight into its liquidity with larger spreads often indicating greater liquidity risk.

AI, being a very heterogeneous class varies in its liquidity characteristics.

■ Illiquidity constrains the ability to rebalance investor portfolios, or react to manager underperformance.

► **Exhibit 7 | Stylized Depiction – AI Strategies Encompass a Broad Liquidity Spectrum**



Downside Premiums. Finally, investors can also make money by assuming the risk of rare but large losses. The complex interactions that can occur during “extreme” events in certain types of alternative investments are difficult to model, but have to be considered; the increase in global volatility and recent unwinding of leveraged trades is a healthy reminder. These are referred to as ‘fat tails’⁹ in statistics colloquial speak. For example, one way insurance companies earn returns-in addition to aggregating and diversifying risk-is by assuming rare event risks. This is the low-probability, yet potentially catastrophic, risk that resides in the left tail of a probability distribution. Insurance companies demand and receive a premium in exchange for underwriting this risk.

Return Drivers

Returns generally come from:

Beta Exposure. In seeking return from fundamental sources or beta, investors hope to earn a risk premium-in excess of the cash or risk-free return-for assuming excess volatility. They face the risk that their portfolio value may fluctuate in response to general macroeconomic conditions.

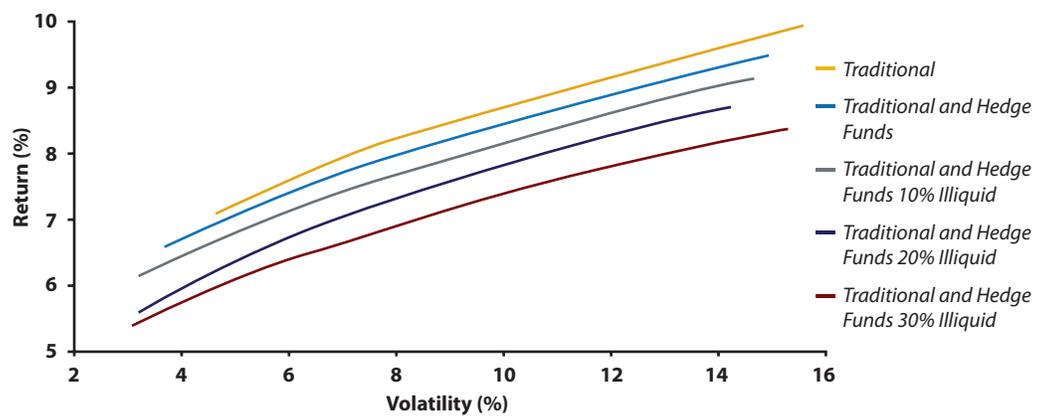
■ AI returns can be viewed as a combination of market exposures and a skill return component.

⁹ Kurtosis measures the degree to which exceptional values — those much larger or smaller than the average — occur more frequently (high kurtosis) or less frequently (low kurtosis) than in a normal (bell shaped) distribution. High kurtosis results in exceptional values that are called “fat tails.” Fat tails indicate a higher percentage of very low and very high returns than would be expected with a normal distribution.

Alpha Exposure. Investors allocate to active hedge fund and private equity investment managers because they believe that they can add skill based returns (alpha) to their portfolio. However, this alpha entails taking active risk, which stems from two sources. First, like beta, alpha itself varies from period to period. This ‘alpha volatility’ represents a unique source of active risk. Further, it is very difficult to judge ex ante whether or not a particular external investment manager is capable of generating alpha; in other words, they face the risk that their prediction, and therefore their selection, may be wrong. The alpha that investors strive to earn may be viewed as compensation for both components of active risk: the alpha volatility and the forecast risk that they are prepared to take.

Restricted Tradability and Illiquidity Premium. Investors who purchase non-traded assets relinquish the ability to liquidate their position. This prevents the investor from pursuing new investment opportunities, meeting unanticipated spending requirements or rebalancing their portfolio. Investors need to be compensated for relinquishing this option.

► **Exhibit 8 | Stylized Depiction – Deriving the Illiquidity Premia**



Rare Event Premiums. Investors who generate returns by providing insurance are exposed to downside risk, or the chance that a low probability outcome can adversely impact portfolio value.

A NEW ASSET ALLOCATION FRAMEWORK

When the asset allocation challenge is viewed from a multidimensional perspective, an investment opportunity can be assigned to one or more return drivers—beta or fundamental returns, alpha or manager skill, illiquidity and assuming rare downside risk. Thinking about investment options in this cross-sectional manner, as combinations of return classes, is valuable from for it allows us to express preferences and make tradeoffs and improves the asset allocation decision.

Rather than thinking of a risk budget as a tradeoff between just risk and return, a new approach would suggest that risk budgeting is the choice of how to allocate risk across the four sources of return. In order to solve the problem of determining exposures and selecting investments, we must recognize that, as in classic approaches to asset allocation:

- Portfolio construction is about linking investor objectives to portfolio choices.
- In making the connection between objectives and portfolios, investors make tradeoffs.

In the classic asset allocation approach, this was done by uncovering an investor's risk tolerance, expressed in terms of the incremental return required for tolerating additional levels of volatility. In the multidimensional approach being proposed here, the problem is slightly more challenging because each return source embeds a different cost. Investors must simultaneously express their preferences across fundamental risk, manager risk, illiquidity and rare event downside risk.

IMPLEMENTING THE FRAMEWORK

In broad terms, there are three steps to this:

Decompose Investments into Classes of Return. As a first step in implementing the new approach, individual investment opportunities may be decomposed to identify how their returns are generated.

Measure Cost Within Each Return Class in a Comparable Manner. Critical to the success of this approach is the ability to explicitly rate costs within each category. For example, fundamental risk is measured using standard deviation. In other words, arrive at appropriate metrics for measuring illiquidity premium, alpha, beta and rare downside risk consistently.

Link Characteristics of Return Classes to Investor Objectives. In a multidimensional framework, appropriate for AI, investors need to consider their tolerance for fundamental risk, active risk, illiquidity and downside risk. This requires understanding how to trade off one return source versus another.

SECTION SUMMARY

We conclude this section by summarizing that the popularity of AI has increased in recent years. Integrating AI into portfolios, however, has been difficult to do in a rigorous manner. A more sophisticated asset allocation approach advocated here seeks

to address a richer set of returns and risk drivers than what is addressed by classical asset allocation models.

ACTIVE MANAGEMENT WITHIN AI

Allocating to skilled external managers with expertise in AI has the potential to improve returns that investors can obtain over time. While demand for skilled managers has always existed, the current focus on alpha is unprecedented, for good reason. Alpha represents a highly diversifiable return source that potentially can improve upon the low-return, high-volatility environment that plagues traditional asset classes. And when properly incorporated into a portfolio, alpha can significantly improve performance.

■ Active managers have more flexibility when defining and executing on investment strategies. AI managers often arbitrage mispricing by formally examining fundamental value and market observed pricing interrelationships.

Unlocking alpha ultimately boils down to choosing skillful managers, which is not an easy task. Moreover, while there are well-developed tools for allocating to beta these tools do not appropriately address the specific characteristics of active managers such as limited histories, changing styles and opaque strategies. To realize alpha's full potential when building a portfolio with active AI managers, investors require forecasting and optimization tools similar to those that are widely used to determine traditional asset class allocations. Despite the current focus on skill-based returns, surprisingly few practical guides exist for investing in active managers in an integrated and analytically rigorous fashion. Critical questions left unanswered by most approaches include:

- How much alpha should be added to a portfolio?
- What is the right combination of alpha sources (active managers)?
- How do allocations to alpha affect allocations to traditional asset classes?

In this section we outline a general framework for active investing that may provide a bridge from theory to practice. This approach:

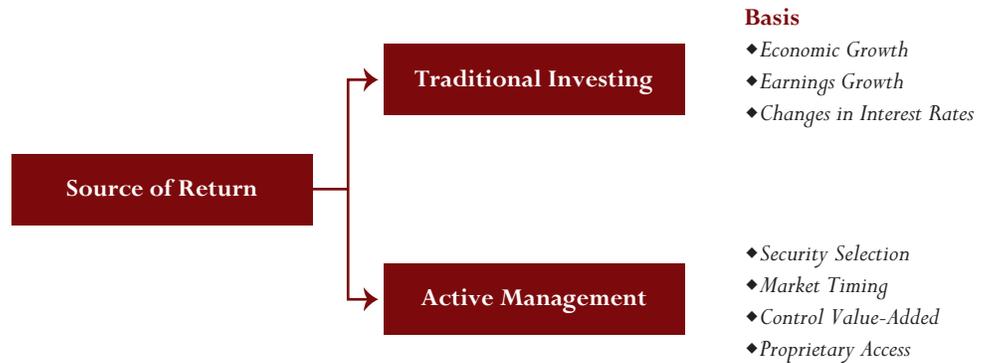
- More accurately assesses a manager's historical characteristics, including skill (alpha) and market exposures (beta).
- Improves forecast of manager performance by combining historical track records with other information.
- Quantifies certain risks particular to active management.
- Constructs integrated portfolios in a way that accounts for various forms of manager risk.

Identifying promising managers, performing due diligence and incorporating subjectivity into forecast remain integral to any successful AI program.

COMPARING BETA AND ALPHA

Conceptually, as alluded to earlier, returns can be divided into alpha and beta components. Thus, a long-only equity manager's return can be divided into the component related to the overall equity market (beta) and the component related to their stock selection (alpha). An index,¹⁰ by contrast, generates all of its return from beta and none from alpha.

► Exhibit 9 | AI Return Drivers Differ from Traditional Investments



Beta and alpha differ across a number of dimensions. Beta is fairly reliable and, therefore, historically has formed the foundation of most investor portfolios. Since beta is tied to macroeconomic growth, as long as economies continue to grow, investors can rely on beta to deliver positive returns over the long term. Furthermore, betas are well-studied and, therefore, are relatively predictable.

Alpha, on the other hand, is much less reliable. Investors cannot depend on a manager to generate positive alpha since, in aggregate, alpha is zero. If one investor generates positive excess returns by purchasing an undervalued stock, another set of investors have necessarily generated negative excess returns by selling the same stock. Furthermore, alpha may degrade over time as the investment environment changes. There is no guarantee that managers who historically have generated alpha will be able to do so in the future.

Given the reliability of beta, why should investors seek to include sources of alpha in their portfolio construction process in the first place at all?

Some Managers Can Consistently Outperform. Although in aggregate alpha is zero, certain managers can consistently generate attractive alpha on a risk-adjusted

■ AI investing is about thinking of views as potential sources of alpha. Views need to be expressed as statements—a stated expected return, some expected volatility, some expected liquidity, some expected relationship with other assets—with some degree of confidence or uncertainty.

¹⁰ Existing hedge fund indices are not fully representative of the universe of hedge fund strategies. Many of them cover a relatively small fraction of the hedge fund population. We estimate that probably only a little more than half of existing hedge funds choose to self-report their performance to one of the major hedge fund databases. Most indexes are equally-weighted and based upon managers' self-proclaimed styles.

basis. For investors who can access them, skilled managers may generate much higher returns per unit of risk than most relatively passive asset class managers.

Alpha Can Provide Diversification Benefits.

- Alphas have low correlation to one another. Alpha is the product of an individual manager’s active decisions. Since these generally differ across managers, alphas typically exhibit low correlation to one another. In addition, because each manager represents a unique alpha source, investors have access to far more alpha sources than beta sources. This implies that even on a standalone basis, combining multiple alpha sources can reduce risk much more dramatically than combining multiple beta sources.
- Alphas are uncorrelated with asset class returns. Adding alpha (or a portfolio of alphas) to traditional equity- and fixed income-oriented portfolios, therefore, can substantially improve risk-adjusted performance if an investor can identify managers’ ex-ante who generate positive alpha.

► Exhibit 10 | Alpha and Beta Drivers Differ

Market Returns	Skill-Based Returns
■ Relatively Consistent Performance on Risk Adjusted Basis	■ Potentially Higher or Lower Performance on Risk Adjusted Basis
■ Limited Number of Sources	■ Larger Number of Sources
■ Moderate Correlation to Each Other	■ Potentially Lower Correlation to Each Other
■ Higher Confidence in Projections	■ Lower Confidence in Projections

CHALLENGES IN FORECASTING AND PORTFOLIO CONSTRUCTION

While the benefits can be compelling, implementing a successful active management program is complex. Asset allocation, whether applied to passive asset classes or active managers, ultimately requires that investors answer and come to terms with two simple questions: **(1)** ‘How will various investment choices perform;’ and **(2)** ‘How can I best meet my investment objectives given my views about future performance?’ Answering the first question is known as ‘forecasting,’ and answering the second question is known as ‘portfolio construction.’ These steps are well-understood at the traditional asset class level, and investors, for the most part, have access to tools that enable them to build portfolios of broadly diversified asset classes. Unfortunately, conventional tools often are inadequate for dealing with the unique characteristics of active AI managers.

These include:

■ Due to the typical asymmetric risk/return characteristics of AI, investing in them warrants a deeper analysis than investing in traditional strategies.

Challenges in Developing Manager Forecasts and Benchmarks. Forecasting manager performance requires that investors first understand historical performance. Unfortunately, standard performance measures such as Sharpe ratios and excess¹¹ return relative to a benchmark can prove misleading. A better approach takes into account the unique set of objectives and concerns that each investor (or a class of investors) has—internally created benchmarks can be effective in meeting safety and liquidity requirements, measuring performance and increasing accountability. For instance, a new approach to savings management may suggest that returns should be benchmarked with an eye to the same sort of variables that influence the judgment of the ‘right’ level of reserves that are available at a certain point of time - in an extreme case, choosing a benchmark with potential capital outflows in mind. The need to be able to properly quantify risks, particularly ‘fat tails’, that AI contain continue to present a special challenge to asset allocators. The challenge of measuring performance is exacerbated when evaluating AI managers, who have significant discretion and no natural benchmark. Often benchmarks in AI tends to be peer group performance.

Characteristics of a good benchmark:

- **Relevance** – At a minimum the benchmark should track those markets and segments of interest.
- **Comprehensiveness** – The benchmark should include opportunities realistically available while measuring the performance of new investments and existing holdings.
- **Replicability** – Total returns should be replicable and must be fair to the investment managers who are measured against it.
- **Stability** – An index may change composition often, and all changes should be easily understood.
- **Expenses** – In the normal course of investing, expenses related to withholding tax, safekeeping, and transactions are incurred. These expenses should be well understood and not be excessive.
- **Simple and objective selection criteria** – A clear set of rules should govern inclusion of asset subtypes.

Within AI, there are many benchmarks that track private equity, hedge funds and real estate. However, measuring historical performance against benchmarks is not enough. Active managers often have limited histories, making it very difficult for investors to separate luck from skill. Even managers with successful track records over long time periods may not be able to repeat that performance if competition increases or if the investment environment fundamentally changes. Alternative investors need a rigorous way to forecast performance that relies on more than just historical data.

¹¹ Investment insights should embody an idea about the market mechanism that explains the origin and sustainability of excess return, and should be supported by systematic analysis of data. Salient examples in equity markets include value and momentum, the overpricing of high-beta stocks, and the overpricing of equity index volatility.

Constructing Portfolios. Once manager forecasts are developed, an investor needs a way to translate these views into an appropriate portfolio. As stressed earlier portfolio construction revolves around making tradeoffs. Given a set of forecasts, investors must make tradeoffs across active managers, as well as between active managers and passive asset classes. Unfortunately, traditional optimizers make tradeoffs across only two dimensions: expected return and volatility. These dimensions do not fully capture other characteristics of active managers that investors care about—such as downside risk, length of track record and general confidence in the sustainability of alpha vs. beta.

CURRENT APPROACHES

Although most investors are aware of the difficulties that have been enunciated earlier with investing in active managers, very few possess tools to systematically address these challenges. Instead, approaches to date have been fairly ad hoc. In contrast to strategic asset allocation, which relies heavily on rigorous statistical modeling, most manager allocation decisions depend largely on experience and judgment. There are at least three popular approaches for allocating to active managers:

Selecting Alpha on the Basis of Beta. One approach has been to divide the strategic portfolio into asset class buckets and choose managers separately within each bucket.

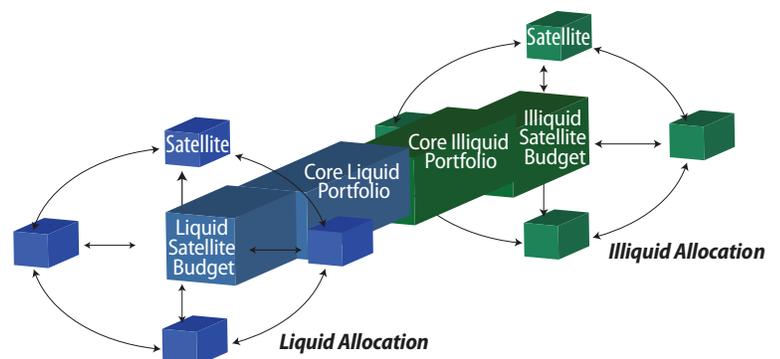
Core-Satellite. While ‘core-satellite’ investing can be implemented in a number of different ways, one popular approach has been to proportionally shrink the strategic benchmark, or ‘core’ portfolio, and allocate the remainder across active managers, or ‘satellites.’ This enables investors to select managers independent of the beta they bring with their alpha. Although this improves upon the approach of choosing alpha on the basis of beta, it prevents the investor from making tradeoffs across the ‘core’ and ‘satellite’ investments. It fails to recognize that the choice of ‘satellite’ investments may change the appropriate ‘core’ portfolio.

■ Properly included in a core portfolio, AI complements listed equity portfolios and has the potential to provide a different source of return, enhance diversification and lower volatility.

► Exhibit 11 | Stylized Depiction – Core Satellite Investing

Satellite Examples:

- ◆ Private Equity
- ◆ Private Real Estate
- ◆ Real Assets
- ◆ Managed Futures
- ◆ Hedge Funds
- ◆ Non-Traded REITs



Portable Alpha. More recently, some investors have adopted a portable alpha approach. Portable alpha allows investors to obtain alpha and beta separately. Investors allocate their capital to what they believe are the best active managers and then obtain their beta exposure synthetically through derivatives. In a portable alpha context unlike ‘core-satellite,’ investors no longer have to make tradeoffs between managers and asset classes. Instead, they can choose the best combination of alpha sources and use derivatives (futures or swaps) to obtain their desired asset class (beta) exposures. While potentially appealing, this approach does not help the investor decide how much alpha to add to the portfolio or determine a suitable combination of active managers.

ADDRESSING ACTIVE INVESTING STRATEGIES IN AI

AI funds have long positioned themselves as ‘absolute return’ strategies, with the ability to generate attractive returns in a variety of market conditions. Accomplishing this ambitious goal requires significant flexibility.

With reduced long-term return expectations for traditional assets, AI funds, often perceived as a pure form of active management, have drawn increasing investor attention. AI managers have a great deal of freedom in exploiting trading approaches and utilize that freedom to change their strategy in order to capitalize on opportunities as they see them. It is precisely this freedom to actively manage their portfolio that has been viewed by many as the primary advantage hedge funds have over more traditional styles of active management; indeed, investors often want their managers to access opportunities where they see them. That said, this freer form of active management is not without its costs. To the extent that such managers can employ dynamic trading strategies, and have more flexibility to execute market timing, it is important for both managers and investors to understand the risks they are exposed to; and whether those risks are ones that generate returns.

A factor that complicates the understanding of portfolio risk is that different assets can contain many types of risks and different levels of portfolio aggregation can highlight different dimensions of risk. In fixed-income portfolios, for example, bonds are often decomposed into their individual cash flows in order to understand their interest rate sensitivity, a primary risk in fixed income portfolios. In order to understand credit or stock specific risk, on the other hand, one may need to focus on the individual companies who have issued particular securities. In global balanced portfolios one may find the most important risks are exposures to different sectors, countries, or currencies. At the most aggregated level there are systematic risks, for example to war, or energy prices, inflation, or global economic conditions, that effect all markets.

■ Strategic Asset Allocation model meets investor goals over multiple market cycles. Tactical Asset Allocation, in contrast, requires flexibility to take advantage of financial markets when opportunities appear to be out of line. It is usually very hard, if not outright impossible, to make quick tactical portfolio tilts.

► **Exhibit 12 | Investing Flexibility Comes at Cost**

A Manager's Ability to Generate Alpha is Primarily Based on Its Investments Strategy

- Leverage
- Short-Selling
- Derivatives
- Illiquid Securities



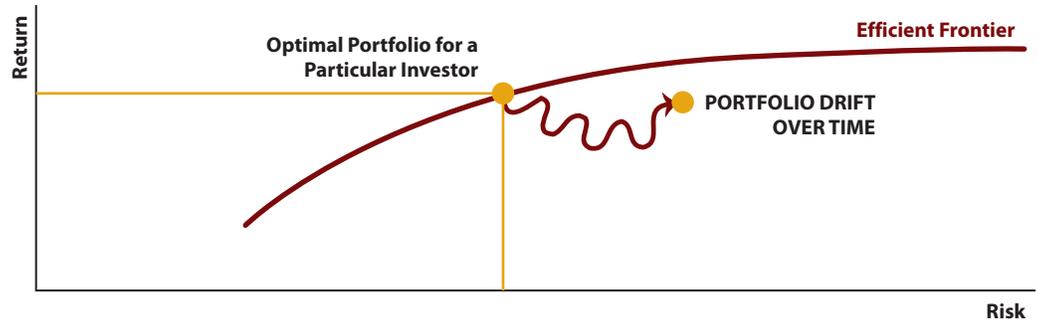
■ These tools, strategies and securities are used by hedge fund managers with the objective of enhancing returns and reducing risks. However, they also increase the risk of losses.

Increased Flexibility for the Manager May Increase Risks to the Investor

While this flexibility can potentially generate value for investors, it also means that active strategies may ‘drift’ substantially over time. This drift could occur in one of three ways:

- **Drift across strategies** – If a manager no longer believes that opportunity exists within a given strategy, the manager may shift towards another strategy.
- **Drift across markets** – Within a given strategy, managers may rotate across sectors or asset classes.
- **Drift within a market** – Depending on their views, managers may significantly change their exposure to a given market over time.

► **Exhibit 13 | Investing Flexibility Creates Portfolio Drift**



These drifts represent short to medium term shifts across asset classes, and therefore can be viewed as market timing decisions. The critical question for investors, though, is to what extent these market timing decisions add value. If AI managers are good at market timing, investors may feel comfortable allowing them to change exposures to different markets as they see fit. On the other hand, if they are poor market timers, these tactical bets could add significant risk to investors’ portfolios without a commensurate increase in returns.

As described earlier, some relatively illiquid AI strategies impose an implicit “cost” on portfolio optimization. In particular, since asset levels are non-reducible in illiquid asset classes, they constrain the ability to rebalance the assets dynamically. This means that as the life of investments unfold, illiquid assets can cause the realized asset weights to vary from the targeted ones. This imposes an implicit cost on the portfolio,

which can be measured as the average distance from the efficient frontier. For this reason, asset allocation assumptions need to be adjusted for the illiquid classes in the form of a haircut to illiquid asset returns distributions. This haircut can be estimated through portfolio simulation, which will provide an estimate of the implied cost of illiquids at different weightings.

A better approach outlined here recognizes that beta and alpha vary across a number of dimensions and that any forecasting and portfolio construction approach should carefully address these differences. This approach consists of four components:

Measuring Performance. The manager's historical returns along with historical alpha, alpha volatility and betas to different asset classes may be taken into account when measuring performance.

Projecting Manager Performance. Since historical data alone can be a flawed predictor of future performance, historical data may be combined with other information to generate more accurate forecasts using Bayesian Statistics approaches.

Quantifying Unique Manager Risks. Investing in active managers exposes investors to new forms of risk, including downside risk and forecast risk. Approaches that explicitly quantify these risks are useful.

Constructing Portfolios. Approaches to portfolio construction in ways that account for more forms of manager risk than seen in conventional frameworks are again useful—notably, an attempt to identify portfolios that will perform well even if the forecasts are wrong.

MEASURING PERFORMANCE

Measuring performance at the manager level is different than at the asset class level. Manager returns are often subject to reporting biases that can obscure comparisons.

Accounting for Measurement Biases. Historical data typically forms the foundation of manager selection and portfolio construction. Unfortunately, the reported returns of many AI managers are subject to biases, preventing comparison between these returns and those of other investments. One bias is return smoothing, or serial¹²

¹² Average serial correlations vary considerably across categories, but five categories have high averages: fixed-income directional (21.6%), convertible fund—long-only (22.5%), event-driven (20.8%), non-directional / relative value (18.2%), and emerging market (18.8%). These categories include some of the most illiquid securities traded; serial correlation seems to be a reasonable proxy for illiquidity and smoothed returns. Moreover, the funds that invest in the most liquid securities—equities and futures—show the weakest average serial correlation: equity hedge funds give (7.8%), and managed futures (-0.1%). These concepts are further explored in Getmansky, Mila, Lo, Andrew W. and Makarov, Igor. *An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns* (2003).

■ Biases in interpreting 'benchmark' returns—All private investment fund databases are biased to some extent, which distorts the picture on true performance.

correlation, which is the correlation of returns in one period with those in future periods. This can occur because active managers who pursue AI strategies can invest in relatively illiquid assets that are not marked-to-market. Since these instruments trade infrequently, investment managers usually do not know the current market prices. Instead, assets may be valued using either an appraised value or historical cost, both of which can artificially smooth reported returns. Return smoothing tends to understate volatility, which overstates historical risk-adjusted performance. Perhaps equally important, smoothing of returns also dampens correlations; this is particularly problematic since it means that market exposures—managers’ betas—will be underestimated and alphas potentially overestimated without correcting the problem. We recommend accounting for this problem by un-smoothing the data to recover the actual pattern of returns over time.

Separating Historical Returns into Alpha and Beta. Once historical data has been adjusted to reflect a more accurate measure of historical returns, one may use regression techniques to estimate each manager’s alpha and beta. Regression compares the movement of a manager’s return with that of asset classes. The regression analysis then splits the return into a component that is related to asset class returns (beta) and one that is independent of asset class returns and driven by manager skill (alpha). If a manager’s returns are related to more than one asset class, regression identifies multiple betas.

PROJECTING MANAGER PERFORMANCE

■ Successful AI managers have attracted capital and investor interest by generating attractive absolute returns.

Projecting returns at the manager level is far more difficult than at the asset class level. Using historical data exclusively to forecast future returns often leads to poor predictions. Separating luck from skill is challenging, especially for managers with shorter track records. In addressing the forecasting challenge with limited data, Bayesian Statistics may be employed, which recognizes that historical performance is only one input. This technique allows investors to combine other information—qualitative views, peer group performance and theoretical considerations—in a quantitatively rigorous fashion. By consolidating the additional information into a view (known as a prior), specifying a confidence level in the prior and blending the prior with historical data, investors can create forecasts that typically are more reliable than those based solely on historical data. One advantage of this approach is that it is fairly intuitive. For managers with long track records, the forecasts will draw primarily from historical performance. For managers with shorter track records, the forecasts will rely more on the prior.

■ While there is definite evidence of superior performance over long periods of time, for most individual strategies, the results are not stable over shorter periods of time. The benefits of proper strategy selection support benefits of manager selection.

Qualifying Unique Manager Risks

When allocating to active managers, investors face an additional risk: the risk that their forecasts can be wrong. Forecast risk is inherent to any portfolio construction exercise. However, investors are able to more safely ignore this risk at the traditional asset class level for two reasons. First, traditional asset classes are well-studied, and investors have a significant amount of data to draw upon when developing forecasts. Second, the chance that traditional asset class forecasts are incorrect is comparable across asset classes (since similar amounts of research and data exist across most traditional asset classes). As a result, forecast risk at the asset class level has relatively little impact on portfolio construction, and most optimization techniques disregard it.

A very different situation exists when forecasting the risk and return characteristics of active managers. Forecast quality is much lower. The differences in forecast quality across managers, as well as between managers and asset classes, suggest that this risk must be addressed. In order to address forecast risk at the manager level, we need a way to quantify this risk. In general, investors may forecast poorly for two reasons:

Limited Information. Intuitively, the less information about a manager, the greater the challenge in forecasting the manager's alpha and beta characteristics. For instance investors would feel more comfortable forecasting the performance of a manager with a five year track record than the performance of a manager with a one year track record. This type of forecast risk is known as sampling error. Approaches are recommended to quantify sampling error by measuring the degree of uncertainty in the alpha and beta forecasts. This uncertainty depends both on the length of a manager's track record and on the amount of additional information an investor possesses.

Incorrect Returns Generating Model. Even with significant amounts of information, investors may generate incorrect forecasts if they use the wrong model for characterizing manager returns. This type of forecast risk is known as specification error. Specification error is more subjective than sampling error; it depends on an investor's assessment of how well he or she understands the manager's return generating process. Lower confidence in the return generating model generally will lead to lower confidence in alpha forecasts relative to asset class return forecasts. We recommend that investors specify a relative confidence level that is directly proportional to the investor's tolerance for active risk (alpha risk) relative to passive risk (asset class risk).

ACCOUNTING FOR DOWNSIDE RISK

When dealing with single managers, many investors are concerned about downside risk. Downside risk refers to the chance of a significant loss. Since many asset allocation

models assume that returns are normally distributed, they underestimate the chance that certain fund strategies will lose money if their return profile is negatively skewed. Not accounting for negative skew results in allocating too much to these strategies.

Investors may account for downside risk in two ways:

First, by recognizing that some managers generate downside risk from exposure to asset classes. For example, certain distressed managers exhibit significant downside risk because they have substantial exposure to the high-yield asset class. In the approach outlined in this paper, since we separate returns into alpha and beta, downside risk from market exposures will therefore not impact alpha estimates.

Second, even after accounting for a manager’s asset class exposures, some managers generate downside risk through their active trading strategies. For example, certain managers may hold very concentrated positions in distressed debt, which would lead to downside risk over and above that found in the high-yield asset class. A technique to estimate this is to compare the shape of a manager’s alpha distribution with that of a normal distribution. We may then penalize the returns of managers who generate downside risk (because their alphas are non-normally distributed) in setting portfolio optimization constraints.

CONSTRUCTING PORTFOLIOS

► Exhibit 14 | Resolving Historical Returns Data Bias in AI

Issue		Implication		Approach
■ Survivorship Bias	→	■ Overestimation of Returns	→	■ Choose Indices that Attempt to Filter out Bias
■ Serial Correlation	→	■ Underestimation of Risk	→	■ Unsmooth Data to Try to Correct for Serial Correlation
■ Strategy "Drift"	→	■ Incorrect Classification of Strategies and Funds, Leading to Bias and Misestimate of Risk	→	■ Aggregate Strategies into More Stable Units
■ Return Forecast	→	■ Forecast Must be Fully Integrated Across Asset Classes	→	■ Use Spreads Where More Stable Over Time
■ Skew and Tail Risk	→	■ Underestimation of Risk and Misallocation	→	■ Theoretically Seeks to Optimize Portfolios Against Skew and Map Back to Mean–Variance Frontier

After developing manager forecasts, quantifying forecast risk and penalizing downside risk, optimization techniques may be used to construct portfolios. Recognizing that manager forecasts are uncertain, a solution may be to Monte Carlo simulate thousands

of possible alpha and beta values for each manager. These simulations provide a range of risk and return outcomes for each candidate manager. After generating these possibilities, investors can choose portfolios that perform well under worst-case scenarios.

Standard optimization techniques try to identify portfolios that maximize some investor objective, such as portfolio Sharpe ratio or investor utility, based on the expected forecasts. In other words, if the investor's objective is to maximize utility, standard optimization techniques will compute the utility for every candidate portfolio and choose the portfolio with the highest value. Such techniques implicitly assume that forecasts are correct, and generate portfolios that perform well if this proves to be the case. If forecasts are incorrect, however, these portfolios are likely to perform poorly.

An approach that generates a distribution of utility values for each candidate portfolio, one of each set of tradeoff possibilities, is a better solution. In contrast to standard optimization techniques, this approach assumes that forecasts may not be correct and explicitly seeks portfolios that perform well in worst-case scenarios. Although the resulting portfolio will be slightly inefficient if forecasts are correct, the investor gains in exchange a measure of protection against forecast risk. This approach is particularly powerful because it allows investors to allocate across active managers, and passive asset classes in an integrated fashion. By contrast, traditional optimization techniques either ignore forecast risk, which leads to unrealistic allocations, or treat asset class allocations and manager allocations as separable problems.

ACCOUNTING FOR TRACK RECORD LENGTH

By finding managers who can consistently outperform a benchmark on a risk-adjusted basis—in other words, who have consistently added ‘alpha,’—investors can substantially enhance portfolio returns. However, many investors face an implicit handicap when trying to accomplish these goals. For example, investors may have rules that eliminate managers with shorter track records.¹³ The rationale for such policies is that the shorter the track record, the less confidence an investor has in ability to project a manager's performance. For managers with extremely short track records, investors often have difficulty separating luck from skill. Although these rules seem prudent, they eliminate potentially attractive managers from consideration.

- While shorter track records may reduce an investor's confidence in a manager's ability to sustain attractive returns, this additional uncertainty simply represents one more form of risk, and this risk can be managed.

¹³ There are many studies that help determine the minimum number of data points or time large enough for skill to emerge from noise. Two portfolios with identical variances, information ratios and tracking errors but differing only in length of history will have different confidence in skill—longer the history, greater the confidence.

■ By arbitraging a combination of market, credit and liquidity risks, AI managers are able to implement a variety of directional and non-directional strategies.

■ Given large dispersion of returns across AI managers and a degree of performance persistence, manager selection is of critical importance

■ By moving to a framework that explicitly incorporates forecast uncertainty in the manager selection process, investors can attempt to tap the benefits from allocating to the widest possible set of skilled managers—while simultaneously seeking to control the risks posed by shorter track records.

In order to create successful actively managed portfolios, investors need to:

- Find managers that have produced high alpha on a risk adjusted basis.
- Combine as many of these managers as possible into a portfolio to diversify active risk (reduce the volatility of a portfolio of alpha sources).

Newer managers may be more attractive than managers with longer track records, for two reasons. First, to the extent that recent managers employ innovative trading strategies, they will face less competition. This implies that not only can they potentially generate higher alphas, but also that these alphas are less correlated to those of other managers. Second, even if managers with longer histories do pursue innovative strategies, the best managers are often closed to new investors. All else being equal, investors may have greater access to newer managers than to more established managers.

Newer managers, however, do create unique challenges for investors. Allocating to these managers requires developing views on their future performance (which is uncertain in any event and very difficult with limited historical data) and accounting for the high uncertainty (or equivalently, low levels of investor confidence) embedded in these views. In sum, investors face a tradeoff when allocating to managers with shorter track records.

A NEW FRAMEWORK FOR MANAGER SELECTION

Investors need a framework that explicitly incorporates forecast uncertainty (which depends partially on track record length) in the manager selection process. By linking track record length to forward looking return variability, investors can compare managers with varying track records in a like-for-like fashion. However, in order to use this approach in practice, investors need to estimate uncertainty in the forward looking views of each manager; in other words, determine how confident they are in each of their forecasts. Conceptually, this uncertainty will depend both on the manager's track record and on the investor's qualitative information about a given manager. This qualitative information could come from a variety of sources, including extensive due diligence, detailed knowledge about the manager's strategy or even a previous working relationship between the investor and manager.

If investors have strong qualitative beliefs about a given manager's ability, track record length becomes less important. Analysis may be used to generate forward looking

views by blending an investor's qualitative beliefs about a manager with that manager's historical performance. By quantifying an investor's confidence in forward looking views, such analysis allows investors to compare all managers in a like-for-like fashion, regardless of their track record length.

SECTION SUMMARY

A prerequisite for constructing any high-quality portfolio is identifying skilled managers who can consistently generate alpha. Although investors intuitively recognize the value of alpha, they generally lack appropriate analytical tools required to build portfolios that include active managers. This section addressed these challenges by suggesting a more rigorous, integrated and, perhaps most important, practical framework that can be implemented for active investing. The approach is unique in that we believe it:

- More accurately measures manager alpha and beta on a historical basis.
- Forecasts manager performance by combining historical data with other information.
- Quantifies specific risks of active managers.
- Accounts for these specific risks when constructing portfolios.

Successful active investment management requires finding and combining multiple sources of skill-based return. However, general rules that exclude newer managers can be counterproductive. They limit the sources of skill-based return and potentially exclude some of the most promising investment strategies. Shorter track records do present additional forms of risk by reducing an investor's confidence in forward looking views. However, by managing this risk intelligently, investors can still incorporate these managers into their portfolios in a rigorous fashion and potentially improve overall performance.

While the details of this approach might require advanced analytical tools, we have tried to summarize the general principals in this section, which we hope will benefit investors even if they use a more qualitative portfolio construction technique.

ALLOCATION NUANCES IN ILLIQUID INVESTMENTS

We now discuss ways for dealing with some important issues in allocating to illiquid assets. The issues with illiquid investments—measuring their risk, rebalancing them and adjusting their levels to individual preferences—have historically confounded attempts to include them appropriately in an overall investment strategy. Some investors have

chosen to simply ignore them. Those taking this route potentially miss opportunities to participate in this asset class.

► **Exhibit 15 | Quantitatively Rationalizing Illiquidity Characteristics**

Issue		Implication		Approach
<ul style="list-style-type: none"> ■ Reported Returns are Inaccurate and Incomplete <ul style="list-style-type: none"> – Not Comparable to Marked-To-Market Returns – Do Not Account for Asset Liquidity Risk – Do Not Account for Tail Risk 	→	<ul style="list-style-type: none"> ■ Misstatement of Returns, Risks and Correlations <ul style="list-style-type: none"> – Not Comparable to Marked-To-Market Returns – Do Not Account for Asset Liquidity Risk – Do Not Account for Tail Risk 	→	<ul style="list-style-type: none"> ■ Create "Marked-To-Market Model" <ul style="list-style-type: none"> – Add Effect for Private, Illiquid Markets to Attempt to Account for Unique Form of Risk – Explicitly Model Tails
<ul style="list-style-type: none"> ■ Rebalancing Costs 	→	<ul style="list-style-type: none"> ■ Limited Ability to Dramatically Rebalance Induces "Portfolio Cost" 	→	<ul style="list-style-type: none"> ■ Apply Haircut Based on Estimated Cost
<ul style="list-style-type: none"> ■ Option Value/Liquidity Preference 	→	<ul style="list-style-type: none"> ■ Unforeseen Liquidity Need Implies Added Risk 	→	<ul style="list-style-type: none"> ■ Include as Constraint in Optimization

A popular approach has been to treat ‘baskets’ of liquid asset classes and illiquid asset classes as separate portfolios. The better-understood liquid portfolio is ‘hived off’ and structured using well-established techniques, and a separate approach is taken in choosing illiquid assets. The problem with this approach is twofold: It ignores the question of how large each of these baskets should be, and it ignores the fact that these two portfolios interact.

Some investors take another road. Without suitably addressing any of the foregoing issues, they simply close their eyes to the allocation problems posed by illiquid asset classes and deal with the portfolio as a whole. The problems created by this approach are obvious: Liquid and illiquid classes cannot be compared to one another in traditional ways, and making inaccurate comparisons will lead investors to inaccurate conclusions about where their money should be allocated. As such, it leaves investors with a nagging question: “Is there any way to take advantage of the potential benefits of illiquid asset classes without risking large investment miscues?” The answer, we believe, is ‘Yes.’ By applying new approaches to the challenges of measuring illiquid risk, rebalancing illiquid assets and tailoring portfolio allocations to individual liquidity requirements, investors can capture the benefits of these assets within an integrated asset allocation framework.

Measurement Issues in Illiquid Assets. Since illiquid asset classes are not traded on a regular basis, valuations and returns are difficult to assess. In short, the prices for these assets are irregularly observed, and therefore are not comparable to those in public markets. Instead, investment managers employ a variety of methods to report their returns. Many, for example, hold investments at the initial book value until they are revalued in the marketplace through the sale of all or part of the asset. Even in

■ An acceptable industry-wide standard for comparing illiquid investments performance does not presently exist. A higher IRR over a shorter period may be based on a small absolute gain.

cases when privately held assets are revalued, there are a wide range of methods for doing so, meaning that reported returns may or may not reflect the true value of the investment. We are left with a problem of comparing one set of assets that are ‘marked to market’—or revalued frequently—to another set, that of assets are valued infrequently. This often leads to an incorrect assessment of the risk level of the investments that are not regularly marked to market. The effect of these two problems—understatement of risk and understatement of correlation—is that investors can over allocate their investments to illiquid private equity.

COMPARING LIQUIDS & ILLIQUIDS

Accounting for Data Issues. A possible solution is to start with the historical, and ‘inaccurate’, reported data, and then clean this data by explicitly incorporating three types of information.

First, to account for the staleness in pricing, we may use a procedure that is sometimes referred to as ‘unsmoothing.’ This involves removing the previous period’s valuations from the current valuations, only looking at the unique change in investment value.

Second, to appropriately capture market volatility, we may incorporate information found in public market indices.

Third, we may choose to include pricing information from the full set of private markets. This is an important step, for while all of these asset classes might be subject to common market risks,¹⁴ different types of alternatives will have very different levels of liquidity risk. In particular, variations in the level of liquidity can be very different in public and private markets, which can create unique risks that we must take into account. This approach will allow investors get a much more reasonable and accurate picture of the real risks and diversification opportunities available among illiquid investments.

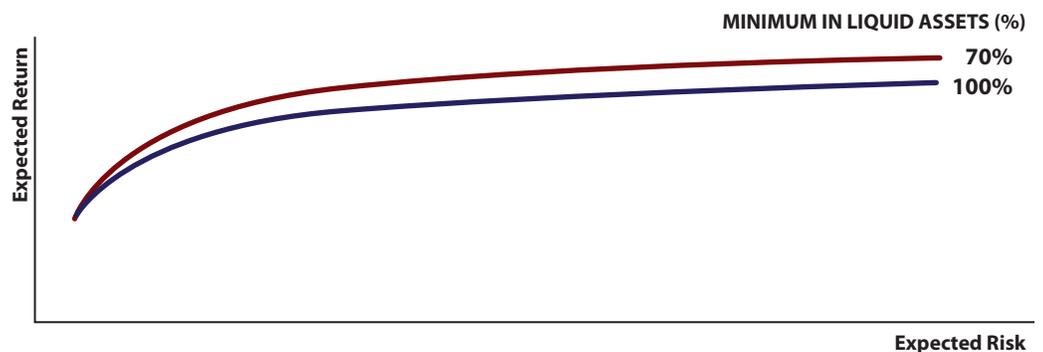
Accounting for Portfolio Rebalancing. When choosing an investment strategy, investors implicitly make dynamic choices. Given their investment objectives, they choose a target allocation level. In practice, of course, certain investments grow faster than others—and the portfolio drifts away from its optimal allocation. The process of ongoing review and reallocation of the portfolio is referred to as rebalancing.

¹⁴ Market risk specifically addresses asset price risk. The market prices of financial instruments in which an AI fund invests can be highly volatile. For instance, price movements of derivative contracts are influenced by, among other things, interest rates, market volatility, the price of the underlying asset or, changes in liquidity conditions. Changes in the financial market environment are often the fundamental cause for price moves, including changing supply and demand relationships, fiscal, monetary and exchange rate policy, or other national and international political and economic events. All these factors are ultimately uncertain and news about them can influence prices giving rise to market price risk.

When all assets are liquid, rebalancing is a straightforward exercise. However, when illiquid asset classes are added to the mix, rebalancing becomes more complicated for illiquidity restricts the ability of investors to buy or to sell. As portfolios drift away from their best possible, or optimized, asset allocation strategies, they might stay there for long periods of time, and investors may be forced to bear the costs of being less than optimally allocated. This represents a constraint imposed on portfolio management, and is considered an implicit ‘cost’ of holding illiquid investments.

■ AI allows investors to unlock the illiquidity premium. This premium is not available to the same extent within traditional investing.

► **Exhibit 16 | Calculating the Illiquidity Premium**



On the basis of this framework, we can construct efficient frontiers in three dimensions—risk, return and liquidity—as illustrated, which contains two frontiers, one for a fully liquid portfolio, the other for a portfolio with only 70% in liquid assets. As can be seen, for a given level of liquidity, the classical relationship that return is increasing in risk is preserved. In addition, however, for a given level of risk, returns also increase as liquidity decreases. This provides a measure of the “illiquidity premium” at a portfolio level. In practice, (and this is strategy specific) we estimate this premium to generate roughly 30–50 basis points of return for every 10% increase in illiquidity in the portfolio (on top of the risk premium).

Once the problem is conceptualized this way investors can try to compensate for it in their initial allocation construction. Based on academic work, we estimate the cost of holding illiquid assets with respect to rebalancing the portfolio ranges between 0.45% and 1.45% in returns on an annualized basis for typical investors holding characteristic portfolios. Now that these costs have been roughly estimated, we may apply a ‘tax’ on our expectations about the returns in these asset classes. What this does in practice is reduce the allocation, in most situations, to illiquid investments. The conclusion is intuitively obvious. Since investors may not be able to sell the illiquid asset classes to rebalance¹⁵ their portfolio, this method leads to smaller initial allocations to illiquids.

¹⁵ Strategic Asset Allocation (SAA) sets investors’ long-term exposure to systematic risk and caters to their risk and return objectives and constraints. Tactical Asset Allocation (TAA) involves short-term adjustments to asset weights based on short term predictions of relative performance across different hedge fund strategies. TAA is an active and ongoing investment discipline, whereas SAA allocations are revisited only periodically, or when the investor’s circumstances change.

■ Investors for whom portfolio liquidity is not a concern may also be able to realize above-average returns arising from illiquidity.

As a result, as the illiquid portfolio holdings grow, they will remain, on average, at the optimal level that investors initially selected.

Accounting for Investor-Specific Liquidity Requirements. Once investors have appropriately accounted for the true risks and costs of investing in illiquid assets, they still must be paid a premium to compensate for investment lock up. One approach might be to reduce expectations of return on illiquid investments by the amount we think we are getting paid for illiquidity. In this way, we attempt to make the illiquid investments more ‘liquid-like.’ There is, however, a drawback to this approach. Every investor’s need for liquidity is unique. Some investors need a great deal of liquidity; others do not. By treating all investors as a ‘market average,’ this approach ignores important differences between investors. A better approach is to tailor the investment strategy to the characteristics of the investor. If the market provides a premium to investors who invest in illiquid investments, those who do not need liquidity should collect the premium, while investors who anticipate needing substantial amounts of cash in the years to come will need more liquidity, and will therefore accept lower returns in exchange for the necessary access to cash. This approach emphasizes that rather than using only one dimension—risk—to classify portfolios for investors, it is also important to use a second dimension—liquidity, which is an investor-specific characteristic that is a crucial input to an asset allocation strategy.

SECTION SUMMARY

It is important to point out that the approaches outlined here will continue to evolve for some time. While considerable work remains to be done, we believe that this conceptual framework for measuring risk in illiquid AI is an important step in addressing investment objectives within a holistic liquid- illiquid context.

CONCLUSION

The alternative investment industry is changing—maturing, expanding and increasing in complexity. At the same time, it has attracted interest from a growing number of institutional and individual investors. Well-managed AI strategies have the potential to offer returns that are superior to those of traditional investments by taking advantage of market inefficiencies. They also allow investors to participate in a wide variety of new financial products and markets not available in traditional investor products. Individual investors have begun to increasingly embrace AI, which, when added to a traditional investments, have the potential to diversify an investor’s portfolio, and have historically had a lower correlation to traditional equity and fixed income investments.

While some individuals tend to invest in more liquid and hedged instruments, others have longer term buy and hold horizons. Integrating AI into portfolios, however, has been difficult to do in a rigorous manner.

A prerequisite for constructing any high-quality portfolio is identifying skilled managers who can consistently generate alpha. Although investors intuitively recognize the value of alpha, they historically have lacked appropriate analytical tools required to build portfolios that include active managers. This paper addresses some of these challenges by suggesting a more rigorous, integrated and, perhaps most important, practical framework that can be implemented for active investing within AI.

