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Asset Allocation: Risk Models for Alternative Investments[1]

Investors have long recognized that asset class returns are driven by the returns to a common set of key risk factors. Asset allocators often use the risk factor approach both to improve portfolio diversification, and to translate macroeconomic views into expected asset returns. In practice, implementing a risk factor approach to asset allocation requires mapping asset classes to their underlying factor exposures. This can be challenging, especially for asset classes where the available historical data is limited.

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This article proposes solutions to measure mark-to-market risk in alternative and illiquid investments. Specifically, we describe how to estimate risk factor exposures when the available asset returns series may be smoothed (due to the difficulty of obtaining market based valuations), and find that alternative investments are exposed to many of the same risk factors that drive stocks and bonds returns.

We recognize that there already is a significant body of literature that attempts to estimate risk factor exposures for various individual alternative investments and strategies. However, little research has been done to estimate the risk factor exposures across all alternatives within an internally consistent, unified risk factor framework. Given increased allocations to alternatives in institutional investor's portfolios, we see an urgent need to develop a consistent approach that directly integrates the risks of alternative assets with the rest of the investor's portfolio.

We classify alternative investments broadly into three groups:

1. Private equity and venture capital
2. Real assets: real estate, infrastructure, farmland, timberland, and natural resources
3. Hedge funds and exotic beta strategies (momentum, carry, value, volatility, etc.)

The lack of mark-to-market data often lures investors into the misconception that these asset classes and strategies represent somewhat of a "free lunch." Their relatively high returns appear to come with low risk and significant diversification to other asset classes in normal times. This misconception arises because return indices for privately held assets often are artificially smoothed, which biases both volatility and correlation estimates downward.

To address this problem, risk models for private asset classes should rely on public proxies or publicly traded equivalents and the statistical methods used to estimate correlation and volatilities must be adjusted to reflect the nature of the reporting biases in the illiquid return series.[2] Investors also need to identify the systematic return drivers that affect each of their alternative investments. If the risk model fails to capture the systematic risk factor exposures, diversification benefits may be over-estimated. An assessment of which factors to include requires the use of econometric methods, as well as judgment.

Econometric modeling of alternative asset classes

A "kitchen sink" regression approach, which starts from a very expansive set of risk factors, however sophisticated it may be, will tend to isolate factors that improve the fit in-sample, but produce exposures without clear economic interpretation. Often, the associated risk models will tend to perform poorly out of sample.[3] For this reason, our approach to assign risk factor exposures to alternative asset classes consists of two steps.

First, we use economic intuition to narrow down the set of factors that should be relevant for a particular alternative asset class or strategy. This process relies on basic valuation principles and knowledge of the underlying investments.

Second, we use econometric techniques to estimate exposures to each of the factors based on historical returns. To adjust for the smoothing effect, our model assumes observed index returns represent a "moving average" of the current and past "true" investment returns. Dimson (1979), and Scholes and Williams (1977) present some of the theoretical foundations for this approach, and we describe our model in detail in the Appendix. For other related but non-factor based methods used to unsmooth data, see also Geltner (1993), Getmansky, Lo and Makarov (2004) and Gallais-Hamonno and Nguyen-Thi-Thanh (2007).

Risk factors for private equity, venture capital and real assets

This two-step process means that before we embark on our empirical analysis, we must identify the most important set of risk factors for each asset class. (Hedge funds require a separate treatment, as explained in the following section.)

If we accept that investors value alternative assets as discounted cash flow streams, we should expect their volatility to be driven by the same factors that drive expected growth and discount factors for stocks and bonds. For assets with stable and less cyclical cash flow dynamics, valuation changes should be dominated by changes in interest rates – just like interest rates drive most of the volatility for bonds – while valuations for more speculative and highly cyclical investments should be driven by changes in the risk premiums that investors require for risky assets and consequently exhibit more equity-like characteristics.

Figure 1 shows an example of the risk factor exposures we use to model private equity and real assets, for 10 generic indices. The table also reports univariate regression equity betas[4], as well as risk exposures for a few sample public markets, for comparison purposes.

Our models directly address the smoothing bias. They are based on an econometric approach that uses transformed risk factor returns that account for the lag structure of the index. We have kept the list of factors parsimonious, and consistent with those used for stocks and bonds. Reported betas represent the sum of the current and lagged betas. Our approach is based on the model discussed by Lo et al. (2005), extended to a multi-factor framework. Derivations and discussion of the model are provided in the Appendix.

FIGURE 1. RISK FACTORS EXPOSURES AND T-STATISTICS FOR PRIVATE EQUITY, REAL ASSETS AND SAMPLE PUBLIC MARKETS

Asset class	Index	U.S. equity	Size	Value	Liquidity (P&S)	Total industry	Nominal duration	Real duration	IG. corp. spread	HY. corp. spread	Equity beta (univ.)
Private equity	Cambridge Assoc. PE	**0.8**	**-0.9**	**-1.4**	**0.2**					**1.2**	**0.9**
		6.5	-1.4	-3.3	1.9					1.5	12.1
Venture capital	Cambridge Assoc. VC	**1.4**		**-3.9**	**0.2**						**1.6**
		5.4		-2.9	0.6						5.8
Infrastructure	UBS Global Infr. & Utilities	**0.5**		**0.7**	**0.2**	**1.1**		**0.6**	**7.3**		**0.6**
		3.8		1.1	1.4			0.4	2.6		5.8
REITs	FTSE NAREIT All Equity	**0.7**				**1.4**		**2.5**	**10.9**		**0.9**
		4.4						1.1	3.5		6.6
Farmland	NCREIF Farmland	**0.1**				**0.9**		**9.7**			**0.0**
		1.0						2.3			-0.2
Timberland	NCREIF Timberland	**0.3**				**2.0**		**9.1**	**2.6**		**0.2**
		1.4						1.2	0.4		1.1
Property (unlevered)	NCREIF Property	**0.3**			**0.4**	**0.5**		**1.2**	**1.7**		**0.3**
		5.2			5.4			1.0	1.3		4.9
Real estate (core)	NCREIF Core	**0.4**			**0.5**	**0.6**		**2.8**	**2.7**		**0.5**
		5.2			4.9			1.8	1.4		5.7
Real estate (value added)	NCREIF Value Added	**0.5**			**0.6**	**1.2**		**2.4**	**3.0**		**0.6**
		4.4			4.3			1.1	1.1		5.1
Real estate (opportunistic)	NCREIF Opportunistic	**0.5**			**0.8**	**1.7**			**11.8**		**0.8**
		3.6			4.7				3.7		5.3
Equities (large cap)	S&P 100	**1.0**	**0.8**	**0.3**							**1.0**
		19.3	1.5	0.8							43.5
Equities (small cap)	Russell 2000	**1.2**	**-2.2**		**-0.1**						**1.1**
		24.5	-5.2		-2.0						18.9
Government bonds	Barclays U.S. Government						**5.1**				**-0.2**
							26.0				-5.3
Corporate bonds	Barclays U.S. Credit					**6.3**			**6.4**		**0.0**
						25.0			25.0		0.6
Inflation-linked bonds	Barclays U.S. Infl. Linked				**0.1**			**5.2**			**-0.1**
					2.3			5.7			-1.9

Numbers in bold are coefficient from regressions estimated on adjusted risk factor returns based on the lag structure in index data (see Appendix for methodology), while numbers in italics are the Newey-West T-Statistics.

From December 1991 through December 2012, Source: PIMCO, Cambridge Associates, NCREIF, Bloomberg.

Analysis based on quarterly data, except for Timberland and Farmland which are annualized due to unreliable quarterly data.

Hypothetical example for illustrative purposes only.

The regressions for Farmland and Timberland are based on annual data covering the period from 12/1991 to 12/2012. The models for all other real assets are based on quarterly data from 12/1991 to 12/2012. A convenient feature of our approach is that annual and quarterly data can be modeled at higher frequency – for example monthly – once assets have been mapped to risk factors for which higher frequency data are available. This process provides an efficient way to combine data of various frequencies into a common correlation matrix, and can help backfill missing historical data (see Page, 2013).

The t-statistics, which we report below each coefficient, are based on the Newey-West (1987) approach, which controls for autocorrelation biases. We show data sources for the risk factor returns in the Appendix.

Private equity, venture capital and real assets are exposed to the following risk factors:

Equity beta represents most of the mark-to-market risk across alternatives, because equity market returns reflect changes in how investors value and discount cash flow streams at a broad level – as evidenced by the recent crisis of 2007–2009.

In a manner consistent to corporate earnings, cash flows for private asset are also linked to general economic growth. Company profitability and earnings growth can be expected to be high during expansions and low during recessions, irrespective of whether a specific company is traded privately of publicly. The same logic applies to real estate and infrastructure investments, whose cash flows – and therefore market values – vary with the level of economic activity.[5]

Other equity factor betas help better capture asset class-specific risk exposures. Our models incorporate style (size and value) and industry-specific equity factors to account for exposures that may be independent of broad equity beta. We source the returns for these factors from Barra (Menchero, Morozov, and Shepard, 2010). Figure 2 shows which industry factor exposures we use for each asset class.

Both venture capital and private equity typically have a small, growth bias, as measured by their sensitivities to these Barra factor returns. Real estate is exposed to the Barra real estate factor. Similarly, many private equity and venture capital investment portfolios may have disproportionate exposure to a specific industry, such as biotech, software or information technology. (Here we do not show industry exposures for venture capital and private equity as this example relies on broad market indices.)

Credit spread duration captures bond-like cash flow risk and financing effects. While equity returns capture some of the common variation in discount rates across alternative asset classes, credit spreads may play a distinct role in shaping the returns for some alternatives such as real estate and infrastructure. Due to the nature of their bond-like cash flows, the pricing of some real assets may fluctuate more directly with bond spreads than with equity valuations. In other words, credit spreads are a key component of the discount rate applied by investors to the cash flow streams of real asset investments because they are viewed in part as substitutes to bonds. In addition, most private equity, real estate and infrastructure portfolios are exposed to financing or refinancing risks. Due to this exposure, anticipated returns can be particularly vulnerable to changes in the costs and availability of debt financing, both of which change with credit spreads.

Real interest rate duration represents the inflation-hedging characteristics of certain alternative asset classes. Real estate investments provide real cash flows that are broadly insensitive to the level of inflation, and nominal cash flows that track inflation over the medium to long term. Rent payments can, for example, be modeled as cash flows that are similar to coupon payments on an inflation indexed bond, since rent changes tend to reflect the general level of inflation. Similarly, managers of infrastructure investments (such as toll roads and electricity producers) often have opportunities to at least partially adjust prices in response to inflation. In the case of real estate, rents are a direct and significant component of inflation thereby strengthening the link. Therefore, real estate and infrastructure investments could be particularly exposed to changes in real interest rates, and less sensitive to changes in nominal rates. But in certain cases, where inflation pass-through is limited, it is appropriate to also consider assigning some nominal duration in the risk factor model.

FIGURE 2. INDUSTRY EXPOSURES AND T-STATISTICS

	Real estate	Food retail	Food products	Paper	Utilities	Transportation
Infrastructure					**0.5**	**0.6**
					2.2	2.0
REITs	**1.4**					
	4.7					
Farmland	**1.3**	**0.3**	**-0.6**			
	4.6	0.7	-1.5			
Timberland	**0.2**			**1.9**		
	0.4			1.9		
NCREIF proprerty	**0.5**					
	3.6					
Real estate (core)	**0.6**					
	3.5					
Real estate (value added)	**1.2**					
	4.8					
Real estate (opportunistic)	**1.7**					
	5.6					

Numbers in bold are coefficient from regressions estimated on adjusted risk factor returns based on the lag structure in index data (see Appendix for methodology), while numbers in italics are the Newey-West T-Statistics.

From December 1991 through December 2012, Source: PIMCO, NCREIF, Bloomberg.

Analysis based on quarterly data, except for Timberland and Farmland which are annualized due to unreliable quarterly data.

Hypothetical example for illustrative purposes only.

Liquidity beta represents an important, yet often overlooked, component of the investment risk of most alternative asset classes. Indeed, decisions to allocate to private and illiquid asset classes are often made without serious consideration to their exposure to liquidity risk. To capture illiquid asset returns' potential exposures to fluctuations in liquidity, we include Pastor and Stambaugh's (2003) liquidity factor to our models for real estate, private equity and infrastructure. The Pastor-Stambaugh factor captures excess returns on stocks with large exposures to changes in aggregate liquidity. Pastor and Stambaugh construct their liquidity measure for each stock by estimating the return reversal effect associated with a given order flow (volume). The idea is that lower liquidity stocks will experience higher return reversals following high volume. They then aggregate these liquidity estimates to form a market wide liquidity measure at each point in time. The return to the liquidity risk factor in a given period is defined by the returns of a long/short portfolio of stocks that have been sorted according to their sensitivity to changes in market liquidity ("liquidity betas"). This methodology is similar to the methodology used to derive the Fama-French (1992) factors.

Recent academic research by Franzoni, Nowak and Phalippou (2012) confirms that realized private equity returns are affected by their significant exposure to the Pastor-Stambaugh liquidity factor. The authors describe the economic channel that link private equity to public market liquidity. They explain how changes in illiquidity affect returns through availability and costs of financing for private equity deals:

> *Due to their high leverage, private equity investments are sensitive to the capital constraints faced by the providers of debt to private equity, who are primarily banks and hedge funds. Therefore, periods of low market liquidity are likely to coincide with periods when private equity managers may find it difficult to finance their investments, which in turn translate into lower returns for this asset class.*
>
> – Franzoni, Nowak, and Phalippou, "Private Equity Performance and Liquidity Risk," Journal of Finance, (2012)

The effect of funding liquidity and market liquidity are not just confined to private real assets. Liquidity conditions should affect the viability of all levered investments and should drive correlation across assets, especially during stress periods. To model a common liquidity beta across alternative assets should help capture this effect.

It should be noted, however, that liquidity exposures are also embedded in spreads and equity returns, hence the coefficients in Figure 2 must be interpreted as exposures to "incremental systemic liquidity," net of the liquidity effect em-bedded in other factors.

Risk factors for hedge funds

To analyze hedge fund style index returns, we expand our list of risk factors. The expanded list consists of both conventional risk factors, such US equity, EM equity, commodity, duration, spread exposures (investment grade, high yield, emerging market), as well as more specialized "alternative beta" risk factors, such as the FX Carry, exposure to volatility, and momentum (trend following).

Figure 3 shows the set of risk factor exposures we suggest for each hedge fund style, based on monthly data from January 1995 to December 2012. All hedge fund style returns are from Hedge Fund Research, Inc. (HFRI), except for Fixed Income Arbitrage and Managed Futures, which are from Down Jones Credit Suisse. The estimated exposures are based on the same regression approach we described for private and real assets. We use this approach because several hedge fund style indices have strong serial correlation in their monthly reported returns, which indicates illiquidity and smoothing of returns (see Getmansky, Lo, and Makarov, 2004). As before, the t-statistics are estimated using the Newey-West (1987) approach, due to serial correlation.[6]

In general, as for other alternative assets, equity beta plays an important role. The motivation for including hedge fund allocations in multi-asset portfolios is generally to diversify and limit exposure to equity risk. It is therefore especially important to estimate the relationship between hedge funds returns and the equity factor, and to evaluate how robust the relationship is likely to be in stressed markets. Most hedge fund styles tend to have significant exposures to equity risk (directly or indirectly) which may lay dormant until a crisis occurs.

For a few hedge fund styles, we do not expect a high equity beta. For example, equity market neutral, managed futures and global macro strategies tend to have equity betas that are statistically insignificant. Short bias strategies is the only hedge fund style that has a very negative equity beta.

Some of the factors play a dominant role in only a few hedge fund styles, but are irrelevant to most others. For example, size and value style exposures play an important role in equity hedge funds, but not in other types of funds.

In general, global macro, equity market and managed futures are the hardest styles to map to risk factors. Managers of hedge funds in these categories allocate risk to discretionary trading and may indeed be long a given risk factor at a certain point and short the same risk factor at another point in time. CTAs tend to follow a set of systematic rules which determine whether they are long or short a market. As a result they may have a considerable long or short exposure to commodities, equities or bond factors at any given point in time, but these exposures are dynamic over time and close to zero on average.

For hedge fund risk analysis and manager selection, the risk factor approach must be complemented by other approaches and cannot replace the due diligence process that provides a more holistic view of individual managers' activities. It may in our view be ill-advised to map an individual hedge fund to risk factors based on its hedge fund style category, because, as mentioned, hedge funds often deviate substantially from their peers of from the average fund in their category. Some of the managers may also be selling or buying options, which gives rise to non-linear factor exposures that only become evident in tail events and crisis episodes. These exposures can be difficult to identify during periods where financial markets are well behaved. Access to short term funding is important

FIGURE 3. RISK FACTORS EXPOSURES AND T-STATISTICS FOR HEDGE FUND STYLES

	U.S. equity	EM equity	Size	Value	Leverage	Liquidity (P&S)	Nominal duration	2-10 steepener	IG. corp. spread	HY. corp. spread	EM. spread	Commodity	Volatility	Momentum	Carry (FX)	Equity beta (univ.)
Hedge fund index	**0.3**	**0.1**	**-0.9**	**-0.2**		**0.03**	**-0.6**		**2.5**	**-0.8**	**0.5**	**0.0**	**0.1**	**0.04**		**0.4**
	8.4	6.4	-6.5	-1.7		1.5	-1.5		3.0	-3.5	3.6	1.8	2.1	2.0		16.8
Fund of funds	**0.1**	**0.1**	**-0.7**	**-0.3**		**0.04**			**3.6**	**-0.6**	**0.5**	**0.1**	**0.1**	**0.1**		**0.3**
	3.6	6.2	-4.6	-1.9		1.7			3.9	-2.6	3.6	2.7	3.3	3.4		11.3
Multi-strategy	**0.1**			**-0.2**			**0.9**		**4.5**	**0.6**	**-0.4**	**0.1**	**0.1**	**0.05**	**0.1**	**0.2**
	3.7			-1.7			2.3		5.2	2.6	-2.4	3.2	3.4	2.2	2.5	8.6
Emerging markets		**0.5**	**-0.4**								**1.1**					**0.7**
		21.9	-2.1								5.3					12.8
Equity hedge	**0.6**		**-1.5**	**-0.3**		**0.1**										**0.6**
	20.1		-7.3	-1.6		1.9										16.9
Long/short equity	**0.5**		**-1.5**	**-0.8**		**0.1**								**0.1**		**0.5**
	15.0		-6.3	-3.4		1.8								2.5		12.2
Short bias	**-1.1**		**3.3**	**2.1**	**2.4**											**-0.9**
	-21.4		9.5	5.7	3.5											-14.2
Relative value					**0.4**				**3.4**		**0.6**				**0.1**	**0.2**
					2.2				7.8		6.4				3.4	11.9
Event driven	**0.4**		**-1.1**			**0.04**			**2.4**							**0.4**
	15.2		-7.7			1.8			4.3							17.4
Fixed income arbitrage							**0.9**	**1.6**	**4.1**	**0.6**					**0.3**	**0.2**
							1.6	2.3	3.3	1.8					4.2	6.9
Global macro		**0.1**				**0.1**	**2.2**		**2.2**		**0.5**		**0.1**	**0.1**	**0.2**	**0.1**
		1.8				1.3	2.6		1.8		1.4		2.0	3.4	2.1	2.6
Equity market neutral	**0.1**		**-0.4**	**0.4**		**0.03**			**1.3**	**-0.5**				**0.1**		**0.1**
	4.6		-2.2	3.1		1.1			1.3	-2.0				3.5		4.7

Numbers in bold are coefficient from regressions estimated on adjusted risk factor returns based on the lag structure in index data (see Appendix for methodology), while numbers in italics are the Newey-West T-Statistics.

Hedge Fund – HFRI Index, Fund of Funds – HFRI Fund of Funds Composite Index, Multi Strategy – DJCS Multi-Strategy Index, Emerging Markets – HFRI Emerging Markets (Total Index), Equity Hedge – HFRI Equity Hedge (Total) Index, Long/Short – DJCS Long/Short Equity Index, Short Bias – HFRI EH: Short Bias Index, Relative Value – HFRI Relative Value (Total) Index, Event Driven – HFRI Event – Driven (Total) Index, Fixed Income Arbitrage – DJCS Fixed Income Arbitrage Index, Global Macro – DJCS Global Macro Index, Equity Market Neutral – HFRI EH: Equity Market Neutral Index.

From January 1995 through December 2012. Source: PIMCO, DJCS, Bloomberg.

Analysis based on monthly data.

Hypothetical example for illustrative purposes only.

to most hedge funds since they rely on significant leverage to achieve their investment objectives or to implement relative value strategies.

We do not explicitly address the risk associated with "forced" deleveraging in episodes of financial crisis, in our risk factor models, but this is an important dimension of the overall "tail" risk for hedge funds. We also note that there is potential for direct or indirect contagion across hedge funds due to the complex, and illiquid nature of the fund activities. These joint dependencies are naturally extremely challenging to model and are beyond the scope of our risk factor analysis.

Putting it all together: risk estimates

Figure 4 compares volatilities based on published index returns with estimated ("un-smoothed") index returns volatilities as estimated from our model, for all alternative investments discussed in this article. Estimated volatility can be decomposed into two components:

- Factor-based volatility. To estimate volatility from risk factors for a given asset class, we use the standard portfolio risk formula, but we replace weights, volatilities, and correlations by risk factor exposures, risk factor volatilities, and risk factor correlations.
- Non-factor based volatility (idiosyncratic risk). We add idiosyncratic volatility such that total volatility matches the un-smoothed index volatility. Idiosyncratic volatility can come from security selection, factor timing, and a variety of other non-systematic, non-factor based risk exposures. This volatility is assumed to have zero correlation with factor-based volatility. The number reported in Figure 4 is the contribution from idiosyncratic volatility.

This analysis reveals, as expected, that volatilities calculated directly from index returns are much lower than those from our un-smoothed estimates. To un-smooth the returns data increases volatility across all asset classes. For certain asset classes, the difference is material. In general, private equity and real assets are more sensitive to the smoothing bias than hedge funds; venture capital, real estate and private equity are particularly sensitive asset classes.

Figure 4 also compares correlation to equities and equity betas for published returns with estimates based on our models. As we assume common risk factors with equities – including direct equity beta – it is not surprising to see that our models generate higher (and we argue, more realistic) equity correlations. We suggest these numbers provide evidence that our models better account for mark-to-market risk.

Takeaways

Mean-variance optimization based on smoothed return indices often suggests extremely high optimal allocations to alternative assets, due to their low realized volatility and low correlation vis-à-vis publicly traded investments in liquid markets. However, our risk factor framework reveals alternative assets actually have significant exposure to the same risk factors that drive stocks and bonds volatility. Returns on alternative assets depend on changes in interest rates, as well as how investors value risky cash flows, as reflected in equity market valuations and credit spreads. Lastly, liquidity and other specialized factors also play a role. In addition to higher volatility, expected drawdowns and tail risk exposures, the risk factor-based approach generally generates higher correlations between alternative investments and their public market counterparts, especially when their equity beta is high.

When our models are applied to portfolio optimization problems the relative attractiveness of alternative assets is consequently reduced. This result lends credibility to our approach. There should not be any systematic "free lunches," and investor's optimal portfolios should not look much different from the total market portfolio. Of course, markets

FIGURE 4. VOLATILITIES, CORRELATIONS AND EQUITY BETAS: REPORTED VS. ADJUSTED

	Volatilities				Equity correlations		Equity betas	
	Reported	Adjusted	Factors	Idiosync.	Reported	Adjusted	Reported	Adjusted
Private equity and real assets								
Private equity	11%	22%	17%	5%	75%	75%	0.5	1.0
Venture capital	25%	52%	26%	26%	41%	45%	0.6	1.4
Infrastructure	15%	17%	12%	6%	56%	56%	0.5	0.6
REITs	22%	27%	20%	7%	61%	59%	0.7	0.9
Farmland	7%	14%	12%	2%	-13%	1%	-0.1	0.0
Timberland	9%	17%	11%	6%	11%	18%	0.1	0.2
Property (unlevered)	5%	13%	9%	4%	13%	52%	0.0	0.4
Real estate (core)	6%	16%	11%	5%	12%	47%	0.0	0.5
Real estate (value added)	9%	21%	14%	7%	16%	49%	0.1	0.6
Real estate (opportunistic)	12%	31%	22%	9%	31%	47%	0.2	0.9
Hedge funds								
Hedge fund index	7%	9%	8%	1%	76%	74%	0.4	0.4
Fund of funds	6%	8%	6%	1%	60%	62%	0.2	0.3
Multi-strategy	5%	7%	5%	2%	45%	39%	0.1	0.2
Emerging markets	14%	18%	16%	2%	67%	69%	0.6	0.8
Equity hedge	10%	12%	10%	2%	77%	75%	0.5	0.5
Long/short equity	10%	12%	9%	3%	66%	64%	0.4	0.5
Short bias	19%	21%	18%	3%	-73%	-69%	-0.8	-0.9
Relative value	4%	6%	5%	1%	59%	55%	0.2	0.2
Event-driven	7%	9%	7%	2%	74%	71%	0.3	0.4
Fixed income arbitrage	6%	9%	6%	3%	33%	41%	0.1	0.2
Global macro	9%	10%	5%	6%	21%	17%	0.1	0.1
Equity market neutral	3%	5%	2%	3%	29%	38%	0.1	0.1

From December 1991 through December 2012, Source: PIMCO, Cambridge Associates, DJCS, NCREIF, Bloomberg.

Analysis for real assets based on quarterly data, except for Timberland and Farmland which are annualized due to unreliable quarterly data. Analysis for hedge funds based on monthly data.

Hypothetical example for illustrative purposes only.

constantly deviate from equilibrium, but nonetheless, portfolio optimization results should reveal our approach is much more in line with financial theory.

We recognize that our risk factor models can only go so far in describing the risk of alternatives assets, but our approach should perform better (in the sense of giving more accurate picture of potential drawdowns and volatility) than simply using artificially smoothed index returns, and it provides a coherent framework to aggregate risk exposures across public markets and alternative investments.

Appendix: Econometric model

The returns to a given asset can be expressed as a linear combination of risk factor returns, as shown in Equation (1):

$$r_t = \alpha + \sum_i \beta_i f_{i,t} + \epsilon_t$$

Where r_t is the return of the asset, a_t is the intercept, β_t is the exposure of the asset to the ith factor, f_i is return for the ith factor , and ϵ_t is an error term. To derive our econometric approach, we assume that the observed "smoothed" returns for each of the illiquid assets can be viewed as a weighted average of the recent history of actual, but unobserved returns, as shown in Equation (2):

$$r_{obs,t} = \sum_j^Q \omega_j\, r_{t-j}$$

Where $r_{obs,t}$ is the observed index return, Q is the number of lags, r_t, is the unobserved actual investment return, and the ω_j's are weights that reflect how past realized investment returns affect the current observed, smoothed return.[7] This model assumes the observed return series, r_{obs}, can be viewed as a so-called "moving average" process of past investment returns, r, with normalized coefficients equal to $\{\omega_j\}$.[8] The observed index return can therefore be written as a function of past risk factor returns, as shown in Equation (3):

$$r_{obs,t} = \sum_j^Q \omega_j \left[\alpha + \sum_i^N \beta_i\, f_{i,t-j} + \epsilon_{t-j}\right] = \sum_j^Q \omega_j \alpha + \sum_i^N \beta_i \sum_j^Q \omega_j f_{i,t-j} + \sum_j^Q \omega_j\, \epsilon_{t-j}$$

Where N is the number of risk factors. If we define $X_{i,t} = \sum_j^Q \omega_j\, f_{i,t-j}$ as the transformed ("moving average") risk factor returns and $\eta_t = \sum_j^Q \omega_j\, \epsilon_{t-j}$ as the weighted error term, it then follows that we can estimate risk factor betas (β_i) on $X_{i,t}$ directly, as shown in Equation (4):

$$r_{obs,t} = \alpha + \sum_i^N \beta_i X_{i,t} + \eta_t$$

The parameters of this joint model of actual and smoothed illiquid asset returns can be estimated in two steps. The lag weights $\{\omega_j\}$ are first estimated with maximum likelihood on observed ("smoothed") asset returns. For each asset an appropriate number of lags are selected based on their statistical significance. In the second step, these estimates for $\{\omega_j\}$ are used to construct the appropriately weighted factor return time series $\{X_{i,t}\}$. The factor loadings β_i are then estimated from Equation (1) using ordinary least squares. Since the error terms, η_t, will be auto-correlated, we use Newey-West corrected standard errors to assess statistical significance for each of the estimated factor exposures.

Data sources for risk factor returns

Equity: S&P 500 total return index, Datastream

Size, value, leverage: Barra GEM II style factor returns

Industry factors: Barra GEM II industry factor returns

Duration: U.S. 10y government yield, Datastream

Corp. spread: U.S. AA yield vs. swap curve, Datastream, PIMCO

HY spread: Barclays U.S. high yield corporate over Barclays Treasuries yield, Datastream

Commodity: DJ UBS Spot, Datastream

Currency: Datastream

Liquidity: Pastor-Stambaugh Liquidity Factor

Volatility: VIX Index (Bloomberg)

Carry (FX): Deutsche Bank G10 FX Carry Basket Spot (Bloomberg)

Momentum: AQR Momentum Total Return Index (Bloomberg)

End Notes

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[2] For example, Pedersen et al. (2011) show that private real estate's risk characteristics closely resemble public real estate's, after the private return series have been appropriately adjusted for "appraisal" biases (see also: Fisher, Geltner, and Webb, 1994, and Fisher and Geltner, 2000). Asness, Krail, and Liew (2001) show the same principle applies to hedge fund returns.

[3] As an illustration of the pitfalls of this approach, Leinweber (2007) used a large dataset of economic data to find factors that fitted the S&P 500. He showed that a model that combined 1) butter production in Bangladesh, 2) cheese production in the United States, and 3) sheep population in Bangladesh explained the returns of the S&P 500 with an r-squared of 99% – clearly a spurious result due to over-fitting.

[4] It should be noted that these betas may be unstable across market regimes. Hence the exposures we report here should be adjusted based on the market environment. An easy way to adjust betas to the current market environment is to focus on past data that represents similar conditions, for example by shortening the regression window to include only recent data, or by using data from a specific regime, such as "turbulent" or "rising rates" regimes. Absent a view on the market regime, we recommend using an unconditional estimate based on data that covers multiple business cycles, which is what we have done here. Doing so will help "identify" a robust set of risk factor exposures for the individual assets.

[5] For example, a recession may reduce demand for office and retail space, which in turn negatively affects the occupancy rates and net operating income of commercial real estate properties. Therefore, changes in prospective equit be positively correlated with changes in projected cash flows from private investments.

[6] As a caveat, while Exhibit 3 presents relatively long-run estimates, econometric methodologies that account for time-varying betas – such as a Dynamic Conditional Correlation-GARCH (Eagle, 2002) model – may help enhance the approach presented here.

[7] Formally, the weights are assumed/normalized to satisfy the following conditions, $\sum_j^Q \omega_j = 1, \omega_j > 0$.

[8] The specification implies a MA (q) process for returns. This approach is based on the additional assumption that actual returns are identically and independently distributed over time. The parameters of the MA (q) process can be estimated using standard software packages. We use the ARMAX-filter function in Matlab [Kevin Sheppard's Econometrics toolbox]. The estimation process also gives us an estimate of the actual unsmoothed investment returns.

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