Alternative Investment Analyst Review

Q3 2016, Volume 5, Issue 2

Call for Articles

Article submissions for future issues of *Alternative Investment Analyst Review (AIAR)* are always welcome. Articles should cover a topic of interest to CAIA members and should be single-spaced. Additional information on submissions can be found at the end of this issue. Please e-mail your submission or any questions to: **AIAR@CAIA.org**.

Chosen pieces will be featured in future issues of *AIAR*, archived on **CAIA.org**, and promoted throughout the CAIA community.

Editor's Letter

You Could be Wrong Even When You are Right!

Suppose you discover an asset that has been losing money since inception (e.g., a mutual fund run by an incompetent manager). Further, you have every reason to believe that the asset will continue to lose money going forward. You wonder how good it would be if you could short this mutual fund. You could not only make some money but also help bring some discipline to the market, removing incompetent fund managers from the market. Well, today is your lucky day, and the SEC has announced that ETFs and inverse ETFs based mutual funds can be created. You immediately call your broker and take a $1,000,000 position in the inverse ETF tracking the fund. The inverse ETF is guaranteed to match the period return on the fund but in opposite direction. So there will be no basis risk – if the fund is down 1% tomorrow, the inverse ETF will be up 1%. Even better, your broker tells you that there is absolutely no cost to buying the inverse ETF, and the broker is even willing to waive its fees. Can it get any better, you think. Yes, it can.

You are a long-term investor and decide to ignore your position completely for the next two years. One day by chance you read the headline that because of poor performance, that incompetent fund manager is about to be fired. It just got even better.

Elated from hearing the news, you login into your brokerage account after two years and notice that your net balance is about $852,000! This cannot be right. You call your broker to find out if there were any mistakes, and you are told that there were no mistakes and that no fees or charges had been made to your account (the fund had not made any distributions during the last two years!). You check the online website to find out about the performance of the mutual fund. You had been correct in your evaluation of the fund manager, as its NAV had declined by 68% during the same 2-year period. The fund manager was indeed quite incompetent. Something must be wrong. How could you have lost $148,000 when you had accurately predicted the poor performance of the fund?

It turns out that you were correct in your prediction, but you used the wrong instrument and were unlucky. The particular path taken by the fund's NAV was such that both long and inverse ETFs ended up losing money. You may think that this is impossible. How could both long and inverse ETFs lose money? After all, it is a zero-sum game, and if long ETF loses money, the inverse ETF must be making money. It turns out that long and inverse ETFs are NOT a zero-sum game. That is, no money is exchanging hands between the two ETF positions. The following simple example demonstrates this issue.

Suppose with equal probabilities our fund can increase by 30% or decline by 35% every six months. The expected semi-annual return on this fund is indeed negative:

$$50\%*30\% + 50\%*(-35\%) = -2.5\%$$

Let us see what could happen to the value of $100 invested in this fund after four periods (2 years).

				286
			220	
		169		143
	130		110	
100		85		**71**
	65		55	
		42		36
			27	
				18

The tree shows that if the fund had increased for four periods in a row, the value of the investment would have grown to $286, while if it had declined every period, the investment would have declined to $18. The last five values that we see represent all possible outcomes of the long position. Of course, they will not occur with the same probability. The following displays the probability tree associated with the above payoffs

				24
			34	
		49		46
	70		66	
100		95		**89**
	135		128	
		182		172
			246	
				332

For example, there is only 6.25% chance that the fund could grow to $286 or decline to $18. On the other hand, there is 37.50% chance that the fund could decline to $71. The expected value of the above five outcomes is $90.36. That is, the fund is indeed expected to lose money after four periods.

Let us now look at the tree for the payoff from inverse EFT.

			6.25%
		12.50%	
	25.00%		25.00%
50.00%		37.50%	
	50.00%		37.50%
50.00%		37.50%	
	25.00%		25.00%
		12.50%	
			6.25%

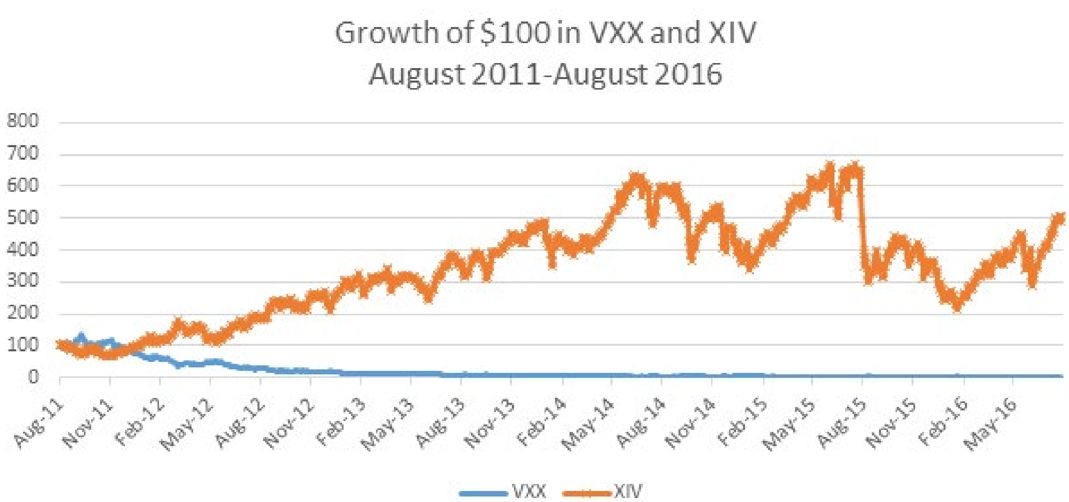
For example, if the fund were to increase during the first period, the inverse ETF would lose 30%, with its value declining to $70. However, if the fund declines in the subsequent period, the inverse ETF will rise to $95. The expected value of the payoffs from the inverse ETF is $110.38. That is, it is expected to make money.

However, notice that there is one possible outcome where both long and inverse positions end up losing money ($71 for long and $89 for the inverse). In fact, this is the most likely outcome! There is 37.5% chance that both will end up losing money.

Two factors are contributing to this puzzling behavior. First, this is a very volatile investment. The high volatility and compounding work together to create highly skewed distributions for both long and inverse ETFs. The extreme positive outcomes are indeed very large for both, but they are less likely to happen than those that are close to the median. In this case, the median turns out to be lower than the initial investment of $100. Second, many investors wrongly believe that an inverse ETFs is similar to a short position in the underlying asset. The above example shows that this is not the case. If fact, if you had shorted the fund at $100, the position would have shown a profit of $29 = $100-$71.

Is it likely to see a similar scenario in the real world? Yes, more often than you may think. Consider these two ETFs: VXX and XIV. VXX is a long volatility ETF while XIV is a short volatility ETF. Their daily returns are a mirror image of each other with only minor differences on a daily basis. However, both ETFs lost money during the last two years, and the loss is not due to fees or other charges. They both lost money because they are highly volatile and the realized price path during the last two years is rather similar to the price path that produced $71 and $89 in our example. In fact, if on August 25, 2014, one person had invested $1,000,000 in VXX and the other person had taken a long position of $1,000,000 in XIV, both would have lost money. The VXX and the XIV positions would be $320,000 and $852,000, respectively. Below is the chart of the two positions since August 2014.

Since a long volatility position provides a hedge against a long position in equity markets, one should expect the long position in VXX to lose money in the long-run; this is indeed the case as it can be seen from a similar chart covering a longer period, August 2011-August 2016. The value of $100 in VXX declines to $1.32 during this period.



The lesson provide by this simple exercise is not confined to long vs. short positions. The important point is that volatility combined with compounding could lead to highly unexpected results. An investment that is expected to earn a positive rate of return could end up delivering a big loss after a few years, if its return is volatile enough, and as shown above, even the one with negative exposure to the asset could end up losing money as well. The other important lesson is that one has to be careful in using derivatives to make speculative or hedging decisions. In the above example, the investor could have selected the inverse ETF to hedge a long position in our hypothetical fund. At first glance, the inverse ETF appears to be the perfect hedging instrument as its rate of return is perfectly negatively correlated with the fund's return. Of course, as we just saw, such a hedging strategy would have backfired as both the long position in the fund and inverse ETFs lost money.

Hossein Kazemi

Editor

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What a CAIA Member Should Know

ABSTRACT: Investors are facing a historically difficult macro environment with significant headwinds felt across various asset classes, impacting return targets. Interest rates are at unprecedented low levels, leading to scant returns for the safest assets and significant principal risk to fixed income returns. Equity markets are trading well above long-term averages exposing investors to downside risk. Additionally, actuarial targets are being significantly lowered, causing balance sheet liabilities to rise at institutionally managed portfolios. Finally, market volatility, which has been exceptionally low in recent years, has increased in the last few months implying pressure on equity returns ahead. Faced with the dual challenges on both the asset and liability fronts, investors today have an increasingly difficult task and are looking into "alternatives", including private equity secondaries ("secondaries"). In this article, the authors suggest that private equity secondaries present an excellent risk-adjusted return profile, exhibiting defensive attributes while still providing attractive long-term returns.

Research Review

ABSTRACT: The notion that patterns in securities prices can be predicted and exploited has given rise to at least two industries: quantitative fund management and, more recently, the index-based alternative operating under the ambitious moniker "smart beta." The performance of such systematic strategies poses a challenge to the "efficient" markets of classical theory, and has therefore produced a third cottage industry for academics—alternatively quantifying, explaining, or refuting the strategies' supposed outperformance. This paper explores the implications and challenges for investors who are interested in extrapolating the past into the future.

ABSTRACT: In this article the authors examine the returns of gold mining stocks, gold, and a diversified portfolio of U.S. stocks over a period from 2006 to 2015. They find that the return on gold mining stocks is explained more by the return on gold than by the return on stocks. Because gold mining stocks are more like gold than like stocks, this suggests that gold mining stocks may be viewed as a substitute for gold in a diversified portfolio. The return on gold, however, is far less correlated with the stock market return than is the return on gold mining stocks. This implies that for risk reduction purposes, gold is preferred to gold mining stocks.

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Introductory Guide to Investing in Private Equity Secondaries

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Introduction

Investors are facing a historically difficult macro environment with significant headwinds felt across various asset classes, impacting return targets. Interest rates are at unprecedented low levels, leading to scant returns for the safest assets and significant principal risk to fixed income returns. Equity markets, which have enjoyed a long expansion post-financial crisis, are trading well above long-term averages exposing investors to downside risk. Additionally, actuarial targets are being significantly lowered, causing balance sheet liabilities to rise at institutionally managed portfolios. Finally, market volatility, which has been exceptionally low in recent years, has increased in the last few months implying pressure on equity returns ahead.

Faced with the dual challenges on both the asset and liability fronts, investors today have an increasingly difficult task and are looking into "alternatives", including private equity secondaries ("secondaries"). As outlined in the following white paper, Capital Dynamics (or “we”) believe that secondaries present an excellent risk-adjusted return profile, exhibiting defensive attributes while still providing attractive long-term returns.

Introduction to the Mechanics of the Private Equity Secondary Market

Private equity funds are typically organized as limited partnerships, to which investors – also commonly referred to as Limited Partners or LPs – commit capital over the course of a fundraising process. The aggregated capital commitments are managed by a General Partner (“GP”) who is responsible for managing the affairs of the fund. A typical private equity fund has an initial duration of 10-12 years, which can be segmented into an investment period (typically the first five years) and a harvesting period (thereafter), during which investments are being exited. By design, private equity funds do not offer redemption

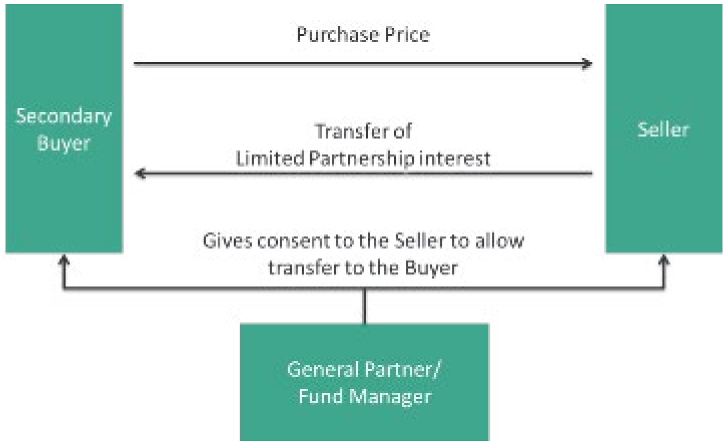


Exhibit 1: Secondary Transaction Steps and Participants
Source: Capital Dynamics, for illustrative purposes only.

or liquidity mechanisms for investors. If an LP needs or wishes to exit a fund prematurely, there is no other way than selling via the secondary market.

In the last two decades, a robust and vibrant secondary market has developed allowing investors to sell their private equity fund positions. A transaction in this "over-the-counter" market encompasses the transfer of a limited partnership interest from the selling Limited Partner ("Seller") to the new owner ("Buyer"), who assumes all rights and obligations of the Seller, including any remaining open commitments to the funds being sold. Typically, this transfer process requires the consent of the General Partner of the respective fund. Exhibit 1 displays a typical secondaries transaction.

The pricing of secondaries is based on the reported valuations that private equity funds publish, typically on a quarterly basis, and is expressed as a percentage of the reported Net Asset Value ("NAV"). Generally speaking, a Buyer and Seller agree upon a valuation date (sometime also referred to as a "reference date") at the start of a transaction. The valuation date (reference date) is an NAV valuation date, and is used to determine the settlement of cash flows (capital calls and distributions prior to the closing date) between the buyer and the seller. Any post-reference date cash flows are taken into account when determining the final purchase price payment at closing. The Seller is typically reimbursed for capital calls, whereas distributions are kept by the Seller and reduce the purchase price payable. Any interim valuation changes to the underlying fund interests typically accrue to the benefit - or detriment - of the Buyer and have no impact on the final payment. Today, after a decade of strong volume growth in the private equity secondary market, there is a wide range of liquidity options and solutions available for private equity investors covering all strategies (buyout, growth equity, venture capital, mezzanine, distressed, real estate, and increasingly infrastructure), investment vehicles, fund maturities and funding levels.

History, Growth, Pricing Evolution and Outlook of the Secondary Market

The root of the private equity secondaries market dates back to the 1980s, when a handful of firms started selectively purchasing private equity interests in leveraged buyout and venture capital funds. It took the market two decades to develop from a niche market – characterized by scarce liquidity, few buyers, distressed sellers and significant discounts to NAV – to a functional and active marketplace featuring meaningful and steady transaction volumes and numerous market participants, including brokers. In 2014, overall transaction volume reached USD 42 billion, six times the estimated transaction volume in 2004, and up more

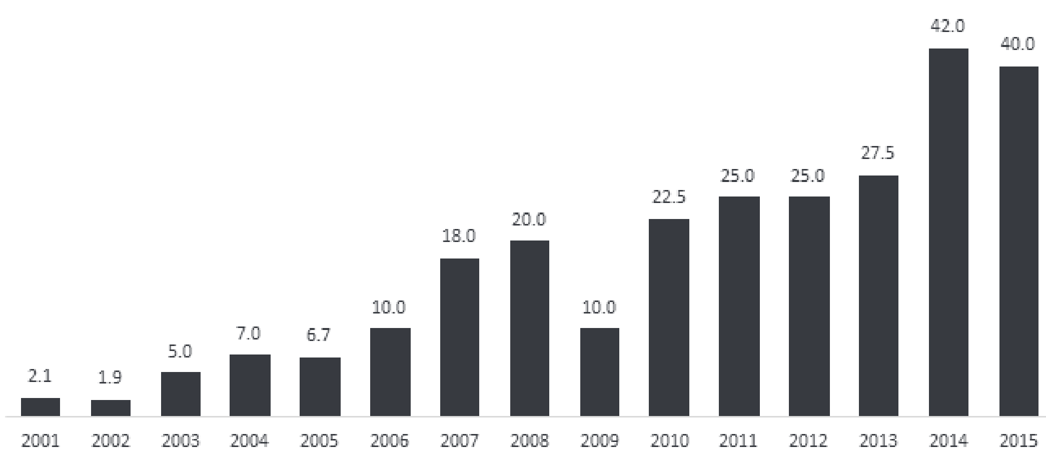


Exhibit 2: Global Secondary Transaction Volume in USDBbillion
Source: Greenhill Cogent, Secondary Market Trend & Outlook, and Capital Dynamics, January 2016

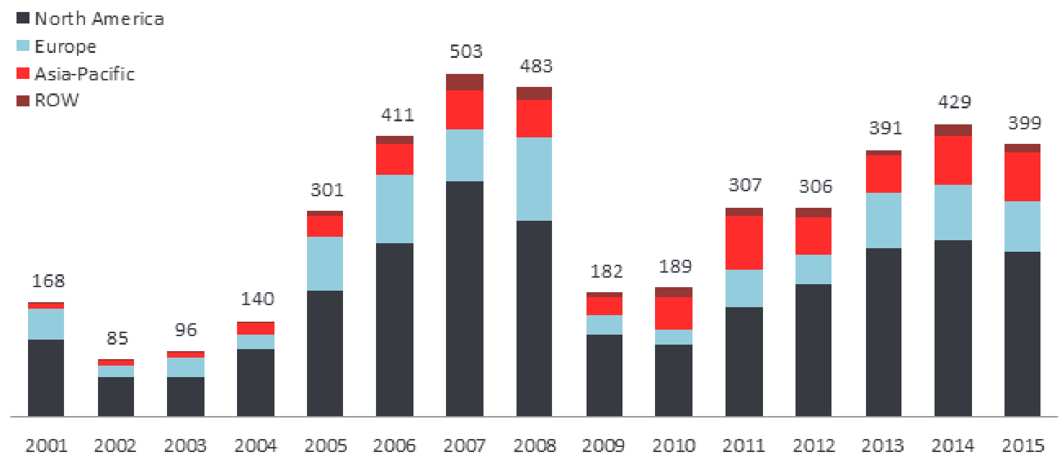


Exhibit 3: Global Private Equity Fundraising 2001-2015 in USD Billion
Source: Thomson Reuters, AVCJ, EMPEA.

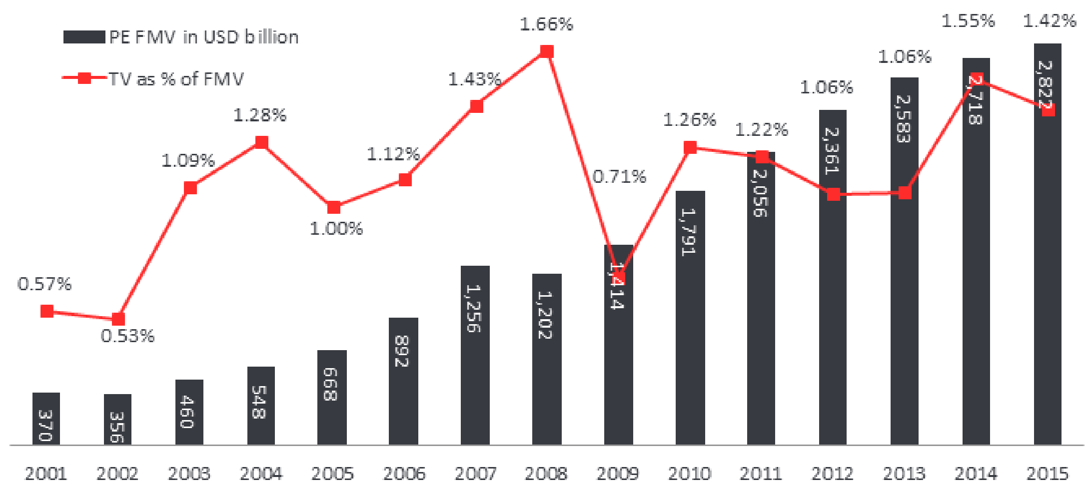


Exhibit 4: Secondary Transaction Volume as % of Unrealized Value of Private Equity
Source: Preqin, Capital Dynamics, April 2016.

than 50% versus 2013. Market volumes in 2015 totaled USD 40 billion, just slightly below the previous year's record of USD 42 billion. This is illustrated in Exhibit 2.

We believe the strong growth since 2005 is the result of a confluence of several factors affecting supply and demand. On the supply side, the main factors driving market volumes, in our view, are the strong fundraising environment from 2005 to 2008 for primary funds, the increased acceptance of secondaries as a portfolio management tool by the private equity community, and – in the wake of the financial crisis – liquidity needs and regulatory changes. The recent price improvements for secondary interests and the availability of leverage for secondary transactions are fueling transaction volumes, particularly for larger transactions.

Acceptance of Secondaries as Portfolio Management Tool: Conversion Rates

Transaction activities in the secondary market are a function of primary fundraising activities. Unless extraordinary circumstances force an investor to dispose of a fund interest shortly after making a primary commitment, a secondary sale usually happens with a time lag of three to five years. The accommodative primary fundraising environment from 2005 to 2008 has translated into the secondary transaction volume in 2009-2013 as shown in Figure 3, and we expect the primary commitments made between 2011 and 2014 will provide additional supply going forward.

Despite very strong transaction volume increases in the secondary market, the proportion of secondary transactions in relation to the unrealized value of private equity is quite small and accounts for less than 2% for the last 14 years. This is shown in Exhibit 4.

Using NAV and unfunded commitments for US and European buyout and venture funds for the previous ten vintage years as the potentially available supply of secondaries and assuming a four-year time lag for primary commitments to be sold on the secondary market, we estimate that merely 1.5-2.0% of commitments made to funds in 2001-2005 have translated into secondary transactions. This conversion rate has increased dramatically since 2005, as secondaries have become a broadly accepted portfolio management tool. We estimate that this conversion rate has reached about 6.2% in 2015 (see Exhibit 5) compared to merely 2.0% in 2005.

Regulatory Changes

Regulatory changes have been broadly discussed in the press and listing the individual pieces of legislation and their individual impact on the supply side of the secondary market would exceed the scope of this paper. Suffice to say that the Volcker Rule, Solvency II and Basel III, in addition to various modifications to local regulatory regimes, have made it more difficult and complex for many traditional, large private equity investors to continue to be invested in the asset class, thus compelling them to sell their existing fund commitments.

Pricing

As briefly described in the introductory paragraph, pricing in the secondary market for fund interests is typically expressed as a percentage of the valuation that is being reported by the fund managers. In a typical secondary transaction, the Seller and the Buyer agree on a valuation date, or a reference date, at the start of the transaction, and the reported valuation for the fund interest as of the reference date forms the basis which prices are based on. This reference date price is then adjusted for subsequent cash flows. It is important to note that changes to the valuations of the underlying funds – unless agreed upon upfront – will typically accrue to the benefit or detriment of the Buyer. Exhibit 7 shows average market pricing for secondary transactions, expressed as the "average high bids as a percent of the NAV" as published by Greenhill Cogent. It is important to keep in mind that these numbers do not represent closing prices for transactions, which can be substantially higher. It is also essential to note that pricing levels can vary greatly, depending on fund age, perceived GP quality, fund strategy and size of the fund interest for sale. Exhibit 6 illustrates the bid dispersion in the first half of 2015 according to Greenhill Cogent.

With that in mind, the published statistics provide an indication of how prices for private equity funds in the secondary market have evolved over time. As illustrated in Exhibit 7, the average high bid from 2006-2007 was above 100% of the reported NAV, i.e. buyers paid premiums to NAVs across all strategies, betting on further appreciation potential for the acquired funds. In 2008,

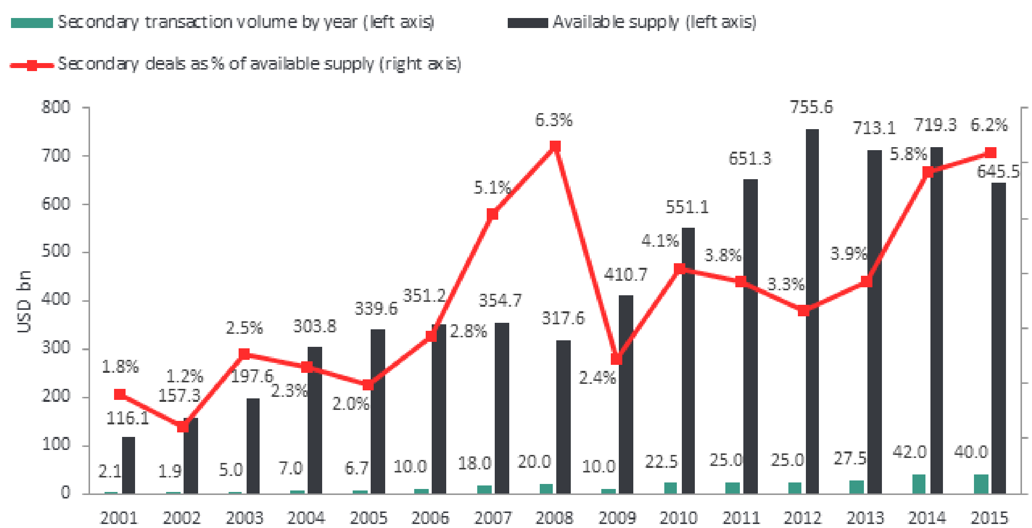


Exhibit 5: Secondary Transaction Volume as % of Available Supply
Source: Thomson Reuters; Greenhill Cogent Secondary Market Trends & Outlook; Capital Dynamics, April 2016.
Methodology: The available supply in any given year is calculated as the aggregated assets (comprising NAVs plus unfunded commitments) of all US and European buyout and venture capital funds for the previous 10 vintage years, applying a lagging effect of 4 vintage years. For example, we compare the 2015 secondary transaction volume (USD 40 billion) with the aggregated supply of all funds of vintage years 2002-2011 (10 vintage years), by summing up NAVs and unfunded commitments of all those funds (USD 645.5 billion) as of year-end.

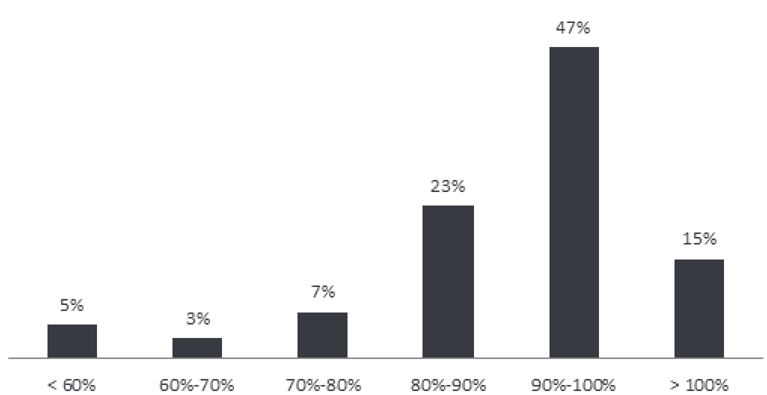


Exhibit 6: All Strategy Bid Dispersion for Recent Vintages
Source: Greenhill Cogent, Secondary Market Trends & Outlook, July 2015.

following the collapse of Bear Sterns in February, the dramatic events in September 2008 and the ensuing 'great financial crisis'; prices in the second half of the year fell sharply and continued to be at a very compressed level through 2009, reflecting widespread financial distress that some Sellers found themselves experiencing while the Buyer community experienced uncertainty and risk-aversion. At the prices offered, only the most liquidity-pressed Sellers actually sold. Consequently, the overall transaction volume pulled back and ended up at an estimated USD 10 billion, or merely 50% of the levels seen in 2008 (see Exhibit 2). In 2010, markets and economies around the world started to recover, as did pricing in the secondary market. Transaction volumes and pricing quickly rebounded to more normalized levels. Since 2010, as market participants became increasingly optimistic, both transaction volumes and initial high bids have risen to 90% of NAV for all strategies in the second half of 2015.

It is possible to replace equity with debt in many ways when financing secondary transactions. In its simplest form, a part of the purchase price is paid in installments after the transaction has already closed and the title to the assets has transferred from the Seller to the Buyer. This form of 'Seller financing' has been employed since inception of the secondary market and is very common nowadays. On the other end of the complexity spectrum is the use of financing structures, where the assets are acquired via special purpose vehicles that are capitalized by tranches of debt and equity. The latter, a more complex form of financing, historically required larger, more broadly diversified portfolios. However, we observe an emergence of levered acquisition structures for smaller portfolio transactions in recent years, as most leverage providers are becoming more comfortable with the asset class. The increasing availability of third party leverage is fueling transaction activity, particularly in the large and mega end of the market. Leverage, if structured and priced properly, can improve equity returns substantially. However, the risk of losing capital for the equity providers can also be exacerbated should the acquired assets not perform as expected.

Demand for Secondaries

Demand for secondaries has increased drastically in the last decade as the market has matured, attracting an increasing number of buyers and investors to the asset class. The buyer universe, which traditionally was mostly comprised of dedicated funds, now includes all investor types who are attracted to the space by the various quantitative and qualitative benefits of the asset class.

Statistics on the composition of the buyer community are scarce, but we believe it is a reasonable assumption that most institutional investors and their consultants are active in the segment. One intermediary estimates that there are more than 1,000 potential buyers including 'non-traditional' or 'opportunistic' secondary buyers[1]. However, survey data published by Evercore, Cogent, and UBS suggest that the bulk of the transaction volume is driven by traditional secondary buyers, secondary funds in particular. This sub-segment of the private equity industry has seen a large influx of capital, as it has become an integral part of asset allocation models for private equity portfolios. Exhibit 8 illustrates the aggregate capital raised by secondary funds according to Preqin, a data provider. Fundraising in the early part of the decade was in line with transaction volumes and relatively muted; aggregate commitments to all funds raised between 2000 and 2004 totaled a mere USD 23.6 billion by 57 funds (compared to an estimated transaction volume of USD 16 billion in the same time period). During the market run-up, 81 funds raised USD 62.4 billion from 2005–2009 (vs. an estimated transaction volume of USD 64.7 billion). Since 2010, driven by some of the same dynamics which drove transaction volumes (see above), there was a total of 137 funds raised between 2010 and 2015 that closed on aggregate commitments of USD 108.6 billion. Total transaction volume in the same period aggregates to USD 182 billion. Today, we believe the supply and demand of capital remain in a healthy equilibrium: we estimate that it would take 14-18 months to fully deploy currently available dry powder if transaction volumes remained at the levels seen in 2014 and 2015.

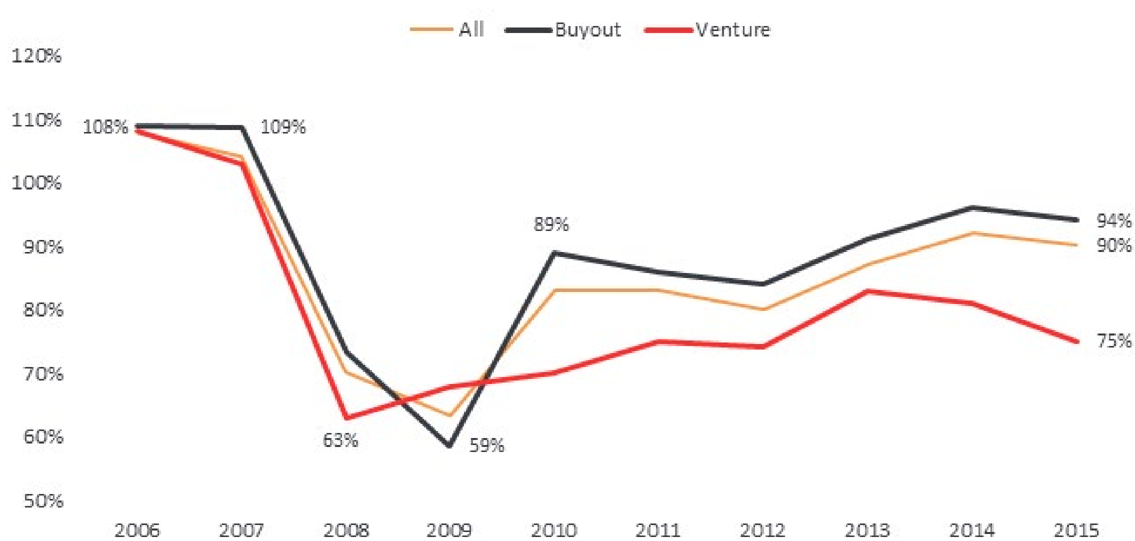


Exhibit 7: Average High Bids as a Percentage of the NAV
Source: Greenhill Cogent, Secondary Market Trends & Outlook, January 2016

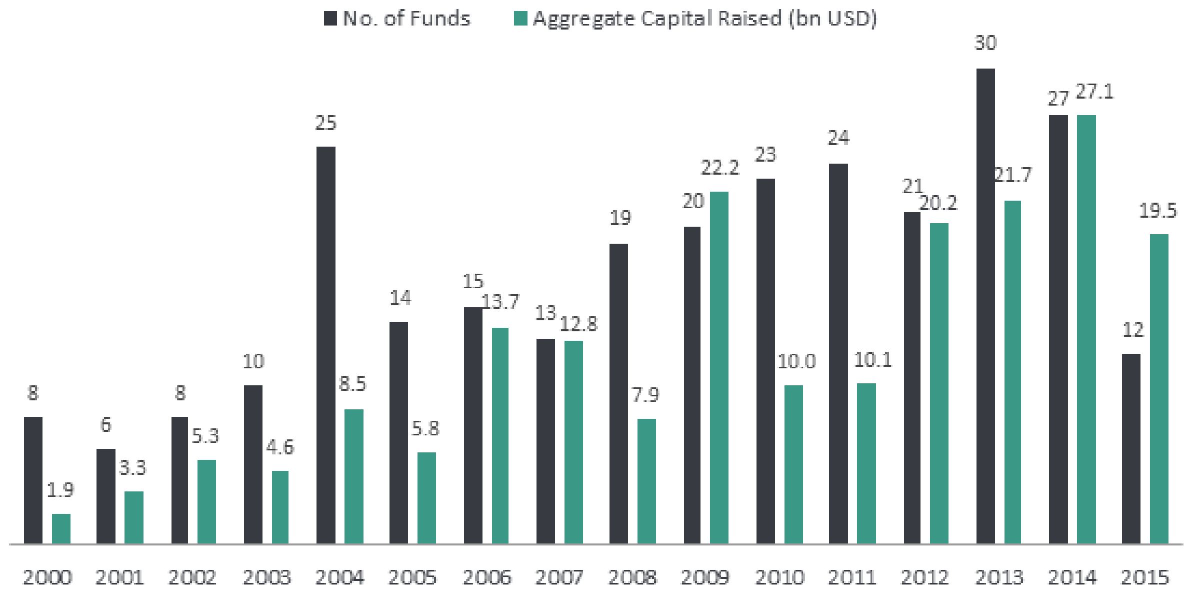


Exhibit 8: Aggregate Capital Raised by Secondaries Funds Since 2000 to 2015
Source: Preqin.

Buyer Types and Market Segmentation

The market for secondaries has evolved to encompass a wide variety of fund specialists based on transaction size, geographic reach, complexity and asset specialization. For investors wishing to access the asset class and analyze and compare results for different funds, it is, in our opinion, necessary to differentiate between providers by transaction size, industry footprint and the flexibility of their respective investment strategies.

Size

The accommodative fundraising environment for secondaries in recent years has allowed a number of groups to raise funds in excess of USD 5 billion, resulting in industry concentration levels previously unknown. These few funds were responsible for the bulk of the capital deployed and the available "dry powder" as illustrated by the 2015 volume break down (Exhibit 9), based on an Evercore survey published in January 2016. According to Evercore, 86% of the 2015 volume was transacted by vehicles larger than USD 1 billion (see Exhibit 9). Conversely, smaller vehicles – USD 500 million and smaller – were responsible for merely 10% of overall transaction volume. Greenhill Cogent estimates that there were eight transactions in 2015 that had transaction sizes in excess of USD 1 billion, representing ca. 30% of overall market volume (2015: 12 and 39%, respectively). The largest reported transaction in 2015 was the partial sale of CalPERS' real estate portfolio with a total estimated transaction volume of USD 3.0 billion. According to a UBS survey – which identified a total transaction volume of USD 33.0 billion for 2015 – 80% of the 2015 transaction volume was moved by 15 buyers. To

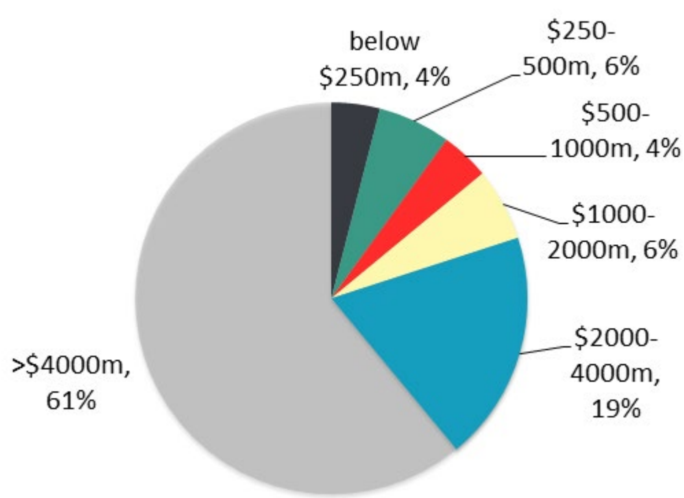


Exhibit 9: 2015 Transaction Volume Split by Size of the Investment Vehicle
Source: Evercore

qualify as one of the top 15, buyers required a transaction volume of at least USD 600 million with an average transaction size of USD 138 million. The UBS survey found that as of December 31, 2015, survey respondents had an aggregate of USD 55 billion of investable capital available between them; 9 buyers had USD 2 billion or more and 7 buyers had USD 1 billion or more. Together, these 16 buyers account for 77% of aggregate "dry powder". Please note that this number excludes a) the possible effect of leverage on available capital and b) near term fundraising goals.

We believe these statistics point to a number of important implications that investors contemplating an allocation to secondaries need to keep in mind:

- As large funds grow, they have to either focus on larger deals or expand their staff in order to effectively deploy capital during their investment periods, or do both. However, even with larger teams and the ability to do more deals in the same amount of time, transactions need to be of a certain size in order to have an impact on the overall performance of the fund and the investment pace.
- The universe of potential Sellers become more constrained the larger prospective deals get, and it is dominated by organizations that have fiduciary obligations to various stakeholders – e.g. pension holders, shareholders, etc. – that require discharge of fiduciary duties. It is hard to imagine, given these fiduciary duties, how any of these Sellers could transact without engaging an experienced broker to run a well-managed sales process in order to maximize value. We believe that the combination of these factors means that the large and mega end of the market is becoming more efficient and expensive, suggesting an increased probability that buyers will suffer from the dreaded 'winners' curse'.

Highly diversified portfolios, by their very nature, are of mixed quality when they are presented to market, thus necessitating that buyers become "index-like" buyers. By contrast, we believe that the smaller end of the market offers more potential to take advantage of inherent inefficiencies and information asymmetries within private equity. Generally, smaller transactions are less frequently intermediated; or if so, then they are intermediated by smaller brokers who do not have the scale and resource base of a globally positioned intermediary active in the large and mega segment of the market. Also, we know that the sheer number of potential Sellers is disproportionally larger in the small to medium market segment. Although some of these Sellers exhibit certain characteristics of larger entities, many are not exclusively motivated by maximizing the price alone: certainty of closing, ease of doing business as well as maintaining confidentiality are important considerations that are less relevant in the larger segment of the market. Consequently, auction processes - if they are run at all – tend to be less efficient and competitive in the small segment compared to those in the larger end of the market. We estimate that the small-end of the market accounted for USD 9-12 billion in annual transactions during the last two years, and is growing faster than the overall secondary market.

Industry Footprint – Integrated vs. Pure-Play Secondary Funds

Secondaries are viewed by General Partners as an opportunity to develop new LP relationships and broaden their roster of investors, in the hope of facilitating future fundraising. As outlined above, GPs typically need to consent to a transfer, which gives them an important tool to manage the composition of their LP base. In general, this favors integrated global private equity platforms with primary, secondary and co-investment capabilities over pure-play secondary buyers, as the integrated platforms are being perceived as future sources of capital by the GP community. Also, integrated platforms can leverage multiple touch-points and regular interactions with a wide universe of GPs globally through a) their investment activities on the primary and co-investment side and b) their standardized post-investment monitoring processes, providing them with the ability to unlock information advantages more quickly and effectively than pure-play secondary houses. Furthermore, being present in the most important markets globally allows for flexible geographic capital allocations, enabling integrated platforms to pick the best relative value available at any given point in time on a global basis.

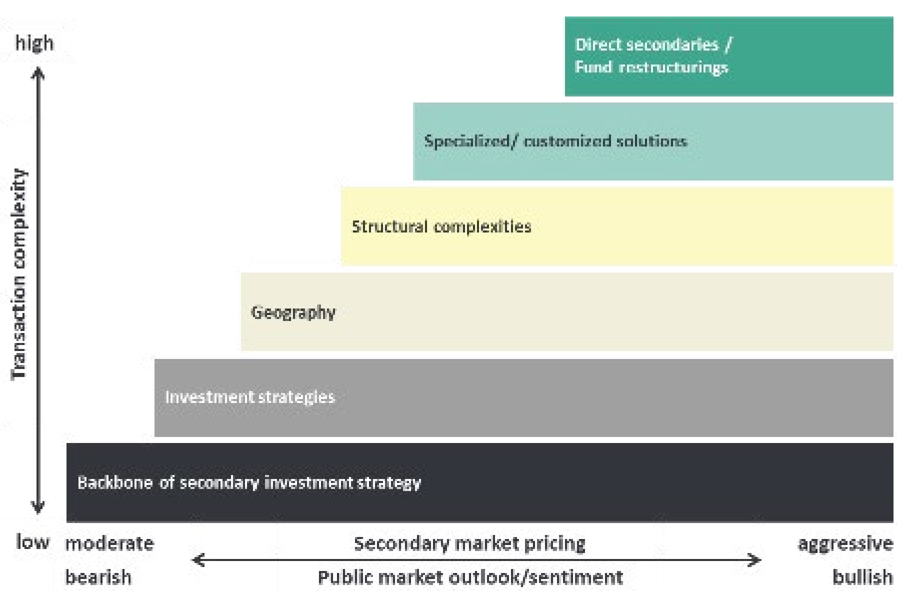


Exhibit 10: 2015 Transaction Volume Split by Size of the Investment Vehicle
Source: Capital Dynamics, for illustrative purposes only.

Strategy Flexibility

Secondary investors that are flexible and able to address various levels of transaction complexities (see Exhibit 10) will have broader acquisition opportunities and be able to create value and deploy capital throughout market cycles at attractive buy-in prices, irrespective of prices for plain vanilla, simple secondary transactions[2]. A secondaries manager who is adept at multiple transaction types is able to flex to market conditions and drive value in a transaction.

Fund restructurings are highly complex and full of conflicting interests and motivations that are often detached from underlying asset performance or quality. Very often, restructurings are the result of an issue that has led to a misalignment of interests between the GP and the LP base. Typically, these do not get addressed until the regular term of the fund has ended. There are usually assets left that exhibit further value creation potential that have not been crystalized yet, offering buyers attractive buy-in opportunities from tired limited partner syndicates.

The possibilities for specialized and customized solutions are endless: from cleaning up orphaned or tail-end portfolios that require a disproportionate amount of resources for the Seller to portfolio recapitalizations/securitizations, there is a vast number of transaction structures and options available in which a Buyer can create value for their investors by providing a solution for a Seller. For example, many private equity investors have to administer mature portfolios. Creating immediate liquidity for these is often challenging and the administrative burden can be onerous, especially if the portfolio includes a high number of partnerships relative to the overall NAV of the portfolio. Implementing structured solutions, however, can bring both administrative relief and provide liquidity while preserving upside optionality.

Structural complexities, such as unusual holding structures or unfamiliar accounting standards, can obscure value. To cut through these complexities and develop an understanding of the opportunities at hand takes time, resources and experience. Larger organizations with a broad bench and resource base are inherently well-positioned to find these 'diamonds in the rough'. However, smaller firms that can also address complexity are of a rarer breed. We believe the smaller firms that can address complexity have a clear advantage in the market, as relatively fewer smaller firms are active in this part of the market.

Furthermore, private equity portfolios typically exhibit broad strategy and geographic diversification, irrespective of their size. A specific focus on areas underserved by the broader secondary fund community, combined with an offering that caters to a specific class of investors – such as geographically-focused, industry/sector-focused secondaries investment strategies – can offer ample investment opportunities and favorable transaction dynamics.

Benefits of Secondaries

Qualitative Benefits

Stand-Alone Benefits

- Enhanced visibility: The higher the funding level of an LP interest, the better the visibility on the underlying asset base and the smaller the blind pool risk. Typically, at the point in time when funding levels are relatively high, there is usually good visibility on the financial and operating performance of the underlying portfolio companies and underperforming investments have either already been marked down or written off. This results in lower loss rates for secondaries investments as illustrated by the results of our quantitative research discussed in the next section.
- Shallower and shorter J-curve effect (if any): In the initial years of a traditional primary private equity investment, a fund will exhibit negative returns inter alia due to the front-loaded nature of the fee structure. This is normal but adversely affects the internal rate of return (IRR). Acquiring a fund interest at a later stage of its life in a secondary transaction, after much of the fee load has already been paid, allows for partial or entire mitigation of the J-curve effect (see Exhibit 11), especially if the interest is acquired at a discount to the NAV.
- Access to certain funds or general partners: By acquiring stakes from the secondary market, a buyer can access funds and/or GP relationships that were not available previously, either because of a missed opportunity during fund raising or because certain fund managers restrict access to their funds in the primary fund raising process but then open up to new investors as a result of secondary sales.

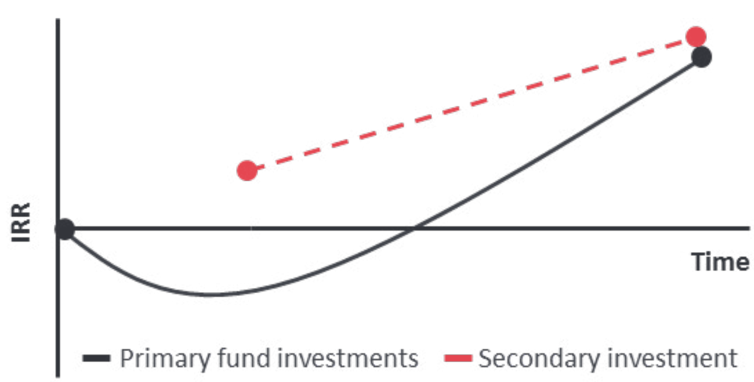


Exhibit 11: IRR Profile of Primary and Secondary Investments
Source: Capital Dynamics, for illustrative purposes only.

- Lower loss rates: As this paper will show in the following section, secondary funds offer lower loss rates than primary funds, as well as generally lower return variability (it should also be noted, however, that the multiple of invested capital for secondary funds is generally lower relative to primary funds).

Benefits in a Portfolio Context

- Accelerated build-up of private equity exposure/faster deployment of capital: By acquiring secondaries, an investor can build up his private equity portfolio faster in a well-diversified manner compared to traditional primary commitments.
- Smoother cash flow profile: Mixing secondaries into a private equity portfolio will smooth out the cash flow profile, especially if the secondaries component is comprised of mature funds with shorter remaining holding periods.
- Diversification: By adding exposure to secondaries, an existing private equity portfolio broadens diversification along all metrics - across vintage years, sectors, geographies/regions, strategies and managers.

Quantitative Benefits

This section presents findings of our analysis of secondaries funds' returns and risk characteristics as well as their liquidity profile in comparison with private equity and venture capital funds. In addition, we looked into return patterns across various secondaries funds' sizes. Analysis are based on data provided by Cambridge Associates and Preqin. Cambridge Associates' dataset consists of performance information for 169 secondary funds and 3,298 global private equity and venture capital funds formed between 1993 and 2011 (Source: Cambridge Associates Secondary Funds Index, Global Private Equity & Venture Capital Index and Benchmark Statistics, as of December 31, 2015). The custom report from Preqin that we used included 142 secondary funds and 2,527 buyout and venture capital funds with known TVPIs, and covered vintage years from 1993 to 2011; that set of data was extracted on June 8, 2016.

Higher average IRR compared to single funds

We found that the average IRR of secondary funds in Cambridge Associates' dataset at 16.7% was higher by 4.1% compared to 12.6% reached by global direct private equity and venture capital funds (see Exhibit 12).

We attribute this higher IRR to a) shorter holding periods in secondary investments (see also Exhibit 16) and b) the recognition of gains through re-valuations of assets that were purchased at a discount.

Slightly reduced TVPI ratios

However, we also found that secondary funds have lower net multiples compared to private equity and venture capital funds. The average Total-Value-to-Paid-in ("TVPI") ratio was 0.17x – or approximately 10% – lower for secondary funds, reaching 1.55x. Private equity and venture capital funds had an average TVPI of 1.72x (see Exhibit 13).

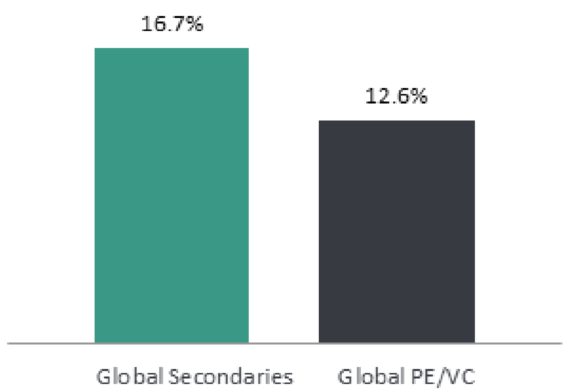


Exhibit 12: Average Net IRR (in%)[3]
Source: See Endnote 3

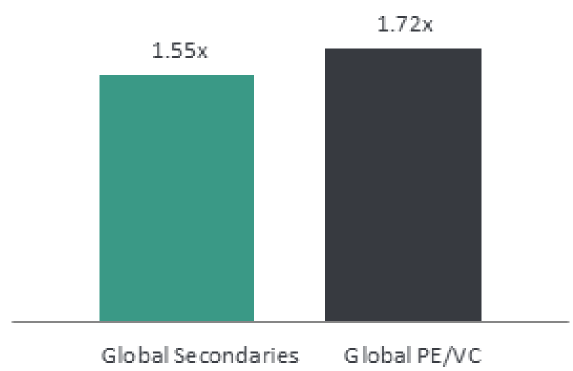


Exhibit 13: Average TVPI Multiple[4]
Source: See Endnote 4

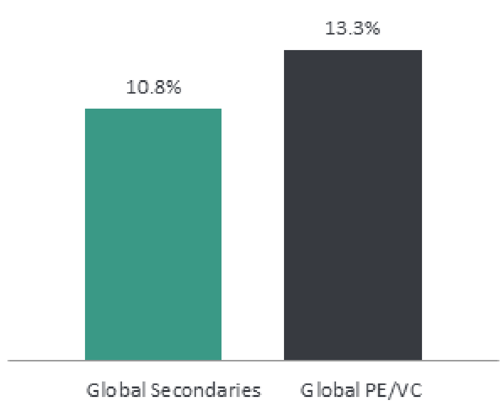


Exhibit 14: Volatility of Quarterly Returns[5]
Source: See Endnote 5

We believe this is due to the fact that secondary purchases are typically being made at a later stage, when the underlying portfolios have already been marked up relative to the original cost basis.

Lower annualized volatility of quarterly returns

Further, we took a closer look at the volatility of global secondary fund returns versus the returns for single private equity and venture capital funds. We found returns from secondaries funds were less volatile on average: 10.8% annual volatility of quarterly returns versus 13.3%.

For this analysis, the annualized volatility of quarterly returns is calculated as the standard deviation on a series of quarterly net end-to-end returns based on cash adjusted NAVs from Q1 1993 to Q4 2015 (92 quarters) and annualized thereafter. The data set used included 196 secondary funds formed between 1991 and 2015, and the Cambridge Associates Global Private Equity & Venture Capital Index included 4,225 global private equity and venture capital funds formed between 1981 and 2015.

We think lower volatility is a result of secondary buyers entering funds at a later stage when compared to the original investor, which allows them to identify and adjust buy-in pricing for underperforming investments.

Fewer Secondary Funds Lose Capital

The following analyses are based on Preqin's Performance Analyst database. We looked at various time intervals and found that over 19 vintage years, from 1993-2011, only 1.4% of secondary funds exhibited TVPI ratios below 1.00x compared to 22.8% for the – significantly larger – set of direct private equity funds. In our view, the greatly diminished risk of losing capital can be attributed to the greater diversification compared to single funds, shorter time to liquidity, reduced blind-pool risk, and last but not least, the acquisition of assets at a discount to NAV.

Accelerated Cash Back

Exhibit 16 compares distributed-to-committed-capital ratios for secondaries and private equity funds as indicators for the respective liquidity profiles.

The analysis is based on a custom report that included 126 secondary funds with vintages from 1998 onwards, and 1,918 buyout and venture capital funds with available DPIs and percentage called information, in both cases between 1999 and 2014.

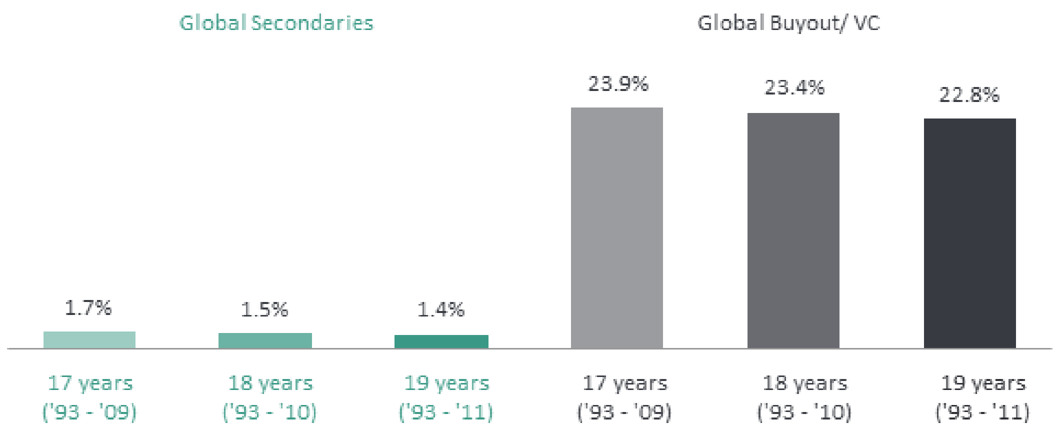


Exhibit 15: Percentage of Funds Returning Less than 1.0x
Source: Preqin, performance data as of December 31, 2015.[6]

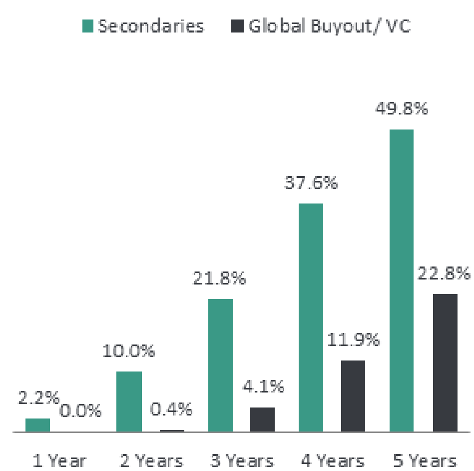
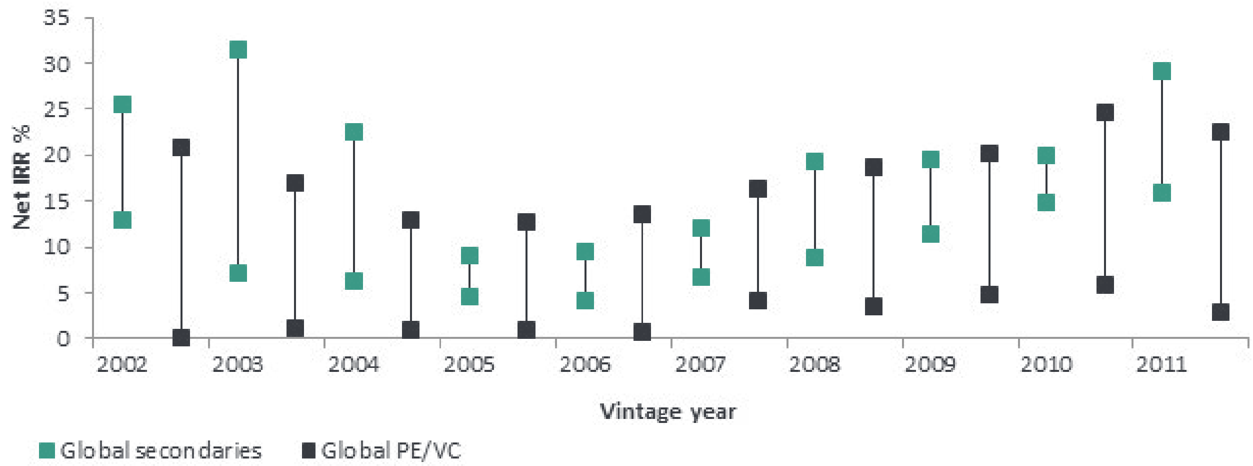


Exhibit 16: Distributed-to-Committed Ratios
Source: Preqin, performance data as of December 31, 2015.[7]



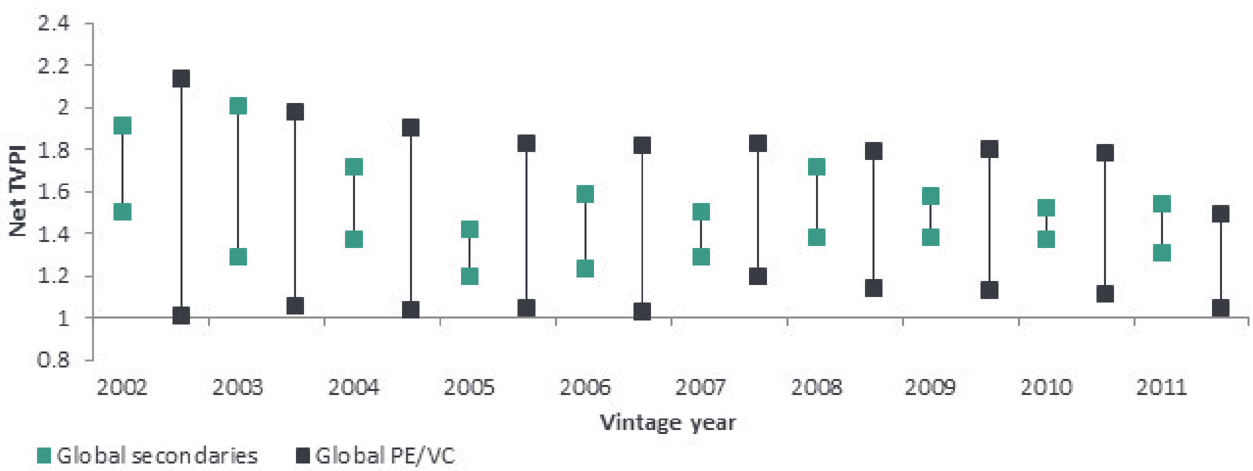


Exhibit 17: Return Dispersion
Source: Cambridge Associates Global Private Equity & Venture Capital Index and Benchmark Statistics as of December 31, 2015. Cambridge Associates Secondary Funds Index as of December 31, 2014. Quartile information for Secondary Funds was not available for vintage years before 2002. 2012 - 2015 vintage year performance is too immature to be meaningful.

As illustrated, secondaries funds typically begin to return cash to investors early at their fund life and show higher distributed-to-committed ratios compared to buyout and venture capital funds for all time periods analyzed. After five years, a median ratio was more than twice as high for secondaries funds as for buyout and venture capital funds.

Narrower Return Dispersion

Exhibit 17 illustrates top and bottom quartile IRRs for secondary funds and private equity funds per vintage year. With very few exceptions, the spread between the top and the bottom quartiles is narrower for secondary funds compared to that of private equity funds. Interestingly, the bottom quartile IRR performance is always a) positive and b) above the level for direct private equity and venture capital funds in the respective vintage years.

Relationship Between Fund Size and Returns

In this section of the paper, we examine if there are any patterns in returns across various fund sizes. We analyzed the sample of secondary funds in the Preqin database formed between 2000 and 2011. We segmented the funds into three categories: small, mid and large-cap, based on their sizes. Due to the growth of the

Vintage	Small-cap Funds	Mid-cap Funds	Large-cap Funds	Total Number
2000-2004	<50m	50m-250m	>250m	30
2005-2009	<300m	300m-1500m	>1500m	55
2010-2011	<500m	500m-2500m	>2500m	20
Number of Funds	34	35	36	105

Exhibit 18: Secondary Funds Sample by Size in USD Million
Source: Preqin. Data was extracted on June 8, 2016.

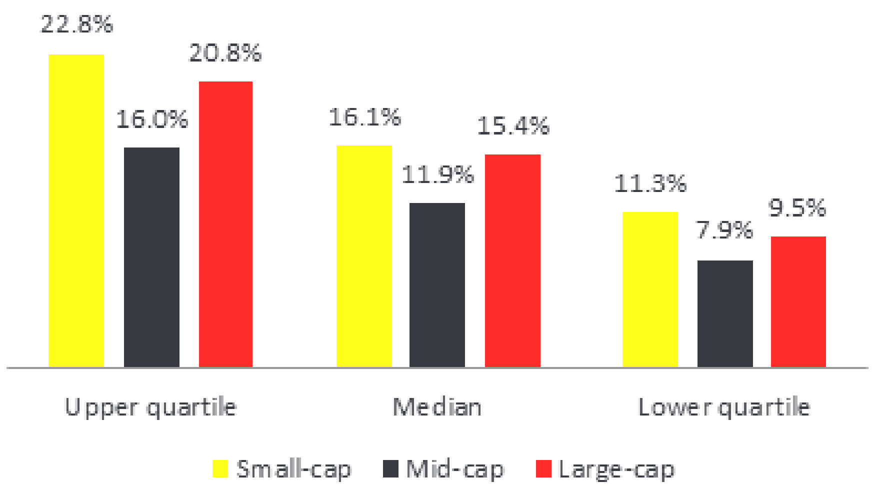


Exhibit 19: Net IRR by Size
Source: Preqin, the most recent performance data up to December 31, 2015. Data was extracted on June 8, 2016.

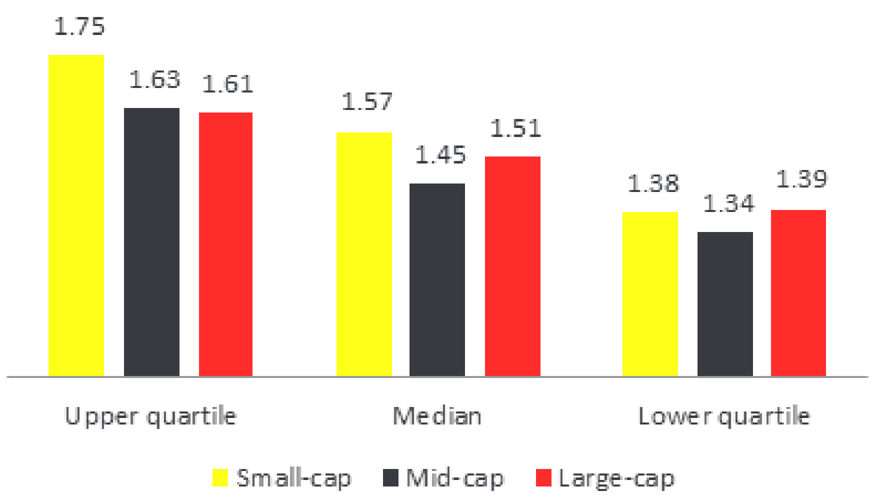


Exhibit 20: Net TVPI by Size
Source: Preqin, the most recent performance data up to December 31, 2015. Data was extracted on June 8, 2016.

market, the fund size segmentation warranted a market evolution approach. As shown below, the segmentation yielded a balanced sample including 34 small-cap, 35 mid-cap and 36 large-cap secondary funds.

Quartile Returns by Fund Size

Quartile returns of secondary funds by size are presented in Exhibits 19 and 20. As demonstrated in these exhibits, small secondary funds outperformed the other fund size categories in terms of net IRRs across all main quartile thresholds. The upper quartile net IRR for small-cap funds was 22.8%, or 6.8 percentage points higher than that of mid-cap funds and 2.0 percentage points higher compared to that of large-cap funds. The same size/return pattern was observed for median and lower quartile thresholds.

In terms of return multiples or TVPIs, small-cap funds outperformed at the upper quartile threshold and at the median level. Large-cap funds demonstrated slightly higher lower quartile returns than other fund sizes.

How to Develop a Secondaries Program

An investor that is new to private equity can start building a private equity portfolio via primaries, secondaries or both. As demonstrated above, we believe that secondaries are well suited to build up diversified private equity portfolios quickly.

Investors wishing to invest in secondaries are faced with a classical 'make or buy' decision. Building an in-house team with secondaries investment experience is costly and takes a long time and is, therefore, not an option for smaller or mid-sized investors. Outsourcing the job of investing into secondaries can be done either via a commitment to a secondary fund or via a separate account solution.

In-house team with secondaries investment capabilities buying limited partnership interests directly

Advantages

- Full control over investment decisions
- Diversification across vintages, geographies and strategies

Challenges

- Time: Building in-house capabilities (sourcing, due diligence, negotiation, transaction execution and portfolio monitoring) can take years
- Cost: It is costly to build an extensive sourcing network that can access most all segments of secondaries
- Decision making process. The decision making process must adjusted so that be accelerated capabilities are developed
- Complex process: Creating monitoring, reporting, compliance processes and capabilities can be complex and onerous

Outsourced solution – investments in private equity secondaries via funds or separate account solutions

Advantages

- Speed: Immediate access to the segment, highly scalable, little to no fixed costs
- Diversification: Outsourced solutions allow for effective diversification across all metrics (vintage years, geographies, strategies)
- Experience: Experienced and professional teams are employed to execute transactions, provide reporting and conduct monitoring

Challenges

- Limited control over investment decisions; nonetheless the provider will invest along pre-defined criteria (increased blind pool risk compared to the in-house approach)
- Additional fee layer; however, the additional fee drag scales up and down with exposure and comes with minimal to no fixed costs

Other Considerations

Discounts Versus Uplift

Some might argue that investing in secondaries is only about acquiring LP assets at deep discounts. We think that acquiring assets at a discount is important, but not the only key to successful secondaries transactions. Further elements to successful secondaries transactions are:

- Deep/long-standing relationships with GPs
- Refined understanding of valuation components and drivers for the acquired assets
- Value creation abilities of GP*s*

Use of Leverage

Some secondary providers apply leverage to their transactions (at the deal and/or fund level) in order to enhance returns. Generally speaking, leverage might lead to higher returns for the equity providers. However, it also has the potential to exacerbate interim adverse valuation movements and increases return volatility.

Concluding Remarks

Secondaries are a highly attractive asset class from a risk/return perspective and on an absolute return basis. We have provided a snapshot of the current state of the market for secondaries and a segmentation framework for investors seeking to access the asset class. Further, we have summarized the qualitative and quantitative benefits of secondaries, both on a stand-alone basis and in the context of private equity portfolios.

The results of our various analyses suggest that secondaries – secondary funds in particular – offer attractive return characteristics making them a valuable, complementary strategy to primary fund investments: historically higher average net IRR, lower levels of volatility, lower number of secondary funds that have lost capital, accelerated cash back and a lower return dispersion all suggest that secondary portfolios have historically generated attractive returns at greatly reduced risk of loss for investors. We believe that the small end of the secondaries market offers the most attractive opportunities for the various reasons outlined herein. Globally positioned managers with integrated primary, secondary and co-investment capabilities offer superior access to the asset class and provide their investors with the benefits of scale and reach. In our view, it is ideal to combine these two factors and access the asset class via a fund that invests in small secondary transactions on a global basis.

Endnotes

1. Source: Setter Capital, 2015.
2. Source: NEPC
3. Source data: Cambridge Associates Secondary Funds Index, Global Private Equity & Venture Capital Index and Benchmark Statistics, as of December 31, 2015. The average IRR is a weighted average based on the number of funds in each vintage year. Capital weighted averages were not used to eliminate large cap bias as capitalization of each vintage year was not available.
4. Source data: Cambridge Associates Secondary Funds Index, Global Private Equity & Venture Capital Index and Benchmark Statistics, as of December 31, 2015. The average TVPI or Total Value to Paid In ratio is a weighted average based on the number of funds in each vintage year. Capital weighted averages were not used to eliminate large cap bias as capitalization of each vintage year was not available.
5. Methodology applied: For the purpose of this comparison, the annual volatility of quarterly returns of the Cambridge Associates Secondary Funds Index and Cambridge Associates Global Private Equity & Venture Capital Index is measured. Volatility is calculated as the standard deviation of a series of quarterly net end-to-end returns based on cash adjusted NAVs for the period Q1 1993 to Q4 2015 (92 quarters) and annualized thereafter. The Cambridge Associates Secondary Funds Index included data for 196 secondary funds, formed between 1991 and 2015, and the Cambridge Associates Global Private Equity & Venture Capital Index included 4,225 global private equity and venture capital funds, formed between 1981 and 2015. Source: Cambridge Associates Secondary Funds Index, Global Private Equity & Venture Capital Index and Benchmark Statistics, as of December 31, 2015.
6. Data was extracted on June 8, 2016.
7. The median ratio of distribution to committed capital (DCC) was calculated based on the distributions to paid-in capital (DPI) ratio and % of capital called by individual secondary, buyout and venture capital worldwide of the vintage years 1998 to 2014 from the Preqin Performance Analyst database. Methodology applied: DPI and % of capital called was not available for secondary funds older than 1998. The custom report included 126 secondary funds and 1,918 buyout venture capital funds with available DPI and % of capital called information as of the year end since 1999 through 2015. Gaps in reporting data for individual funds do not significantly distort results based on a test performed with a carry forward of DCC ratios for previously reported periods. Source: Preqin. Data was extracted on June 8, 2016.

Authors' Bios

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Senior Director
Investment Management
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Jochen is a Senior Director on the Secondaries team in Investment Management at Capital Dynamics. He has 11 years of experience in private equity and finance, and has been involved in secondary and primary investments across the entire private equity spectrum including buyouts, venture capital, energy and distressed debt in Europe, the US, Asia and Latin America. Jochen holds a Diplom Kaufmann degree with honors from the University of Regensburg.

Joseph B. Marks, CFA
Managing Director
Investment Management
Capital Dynamics

Joseph is a Managing Director and Head of Secondaries in Investment Management at Capital Dynamics. He has 18 years of experience in private equity. Prior to joining us, Joseph was a principal at Coller Capital in New York where he was responsible for the origination, evaluation, and execution of secondary portfolio transactions. He holds a Bachelor's degree in Economics (Honors) from Stanford University, and an MBA and a Juris Doctor in Law from the University of California, Los Angeles. Joseph also holds the professional designation of Chartered Financial Analyst (CFA).

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Kairat is a Senior Vice President in Research at Capital Dynamics. Previously, Kairat worked as a financial controller with Burckhardt Compression AG, a Swiss international engineering group. Kairat holds an honors degree in Economics from the Kazakh State Academy of Management, an MBA in Finance from St. John's University and has completed a management training program at the University of St. Gallen.

The Persistence of Smart Beta

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S&P Dow Jones Indices

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Index Investment Strategy
S&P Dow Jones Indices

"Knowledge of the fact differs from knowledge of the reason for the fact." – Aristotle

The notion that patterns in securities prices can be predicted and exploited has given rise to at least two industries: quantitative fund management and, more recently, the index-based alternative operating under the ambitious moniker "smart beta." The performance of such systematic strategies poses a challenge to the "efficient" markets of classical theory, and has therefore produced a third cottage industry for academics—alternatively quantifying, explaining, or refuting the strategies' supposed outperformance. As funds or indices gain in popularity and usage, or as academic papers exploring their themes are celebrated, there is frequently a resultant change in performance. This creates a particular challenge for investors interested in extrapolating the past into the future.

At a general level, there are two (not mutually exclusive) reasons that explain why a particular strategy might outperform, above and beyond sheer luck.[1] The first reason is that the outperformance might simply be compensation for increased risk. For example, Fama and French[2] famously documented that cheap stocks outperform more expensive stocks over time. Perhaps this effect arises because cheap stocks are more volatile than expensive ones—in which case one might argue that the effect is simply a reward for bearing the incremental risk of cheapness. On the other hand, a strategy's incremental performance might not be a compensation for risk, but might represent a true anomaly.[3] In our example, this would imply that the incremental outperformance of cheap stocks *more than* compensates for their putative higher risk.

The question of whether the incremental returns attributed to a given factor (e.g., the outperformance of stocks with high momentum or low volatility) will persist is impossible to answer definitively. Yet investment vehicles tracking non-standard indices have become increasingly popular.[4] The vast majority posit both the *existence* and *persistence* of an anomaly in the market (the undervaluation of value stocks, for example) and systematically exploit them. When evaluating such investments, investors ranging from the individual to the largest institution must ask themselves not only if a particular vehicle is well-designed to exploit the anomaly but, first, if the anomaly is expected to persist?

We argue that the third industry—academic research—can have a material impact on factor persistence.[5] We illustrate this by identifying four distinct types of anomalies, only two of which show any degree of persistence.

- As the name suggests, **disappearing anomalies** don't last. The disappearance category includes strategies whose returns are arbitraged away after discovery, indicating that the returns themselves are neither a compensation for risk nor difficult to replicate. In such cases, once the average investor becomes aware of the anomaly, its benefits are completely eroded.
- Worse yet are **statistical anomalies**. Here we illustrate the pitfalls of investing based on spurious relationships that appear to exist due to chance. In these circumstances, expecting a predictable pattern of returns to emerge is naïve; we caution against the high false-positive rate to be expected with modern computing power.[6]
- Moving to the positive side of the ledger, we consider **attenuated anomalies**, the risk-adjusted returns of which diminish as they become more widely known. Attenuation shows the importance of assessing returns on a risk-adjusted basis; seemingly persistent returns may simply be a compensation for bearing additional downside risk.
- Finally, there are **persistent anomalies**. This final type shows that persistent returns can exist, even after adjustment for risk—and reminds us of the importance of conducting risk analysis to distinguish the character of anomalies.

This is not a purely academic exercise, as these four categories provide investors with a toolkit to use when assessing the anomalous returns on various strategies. In particular, we hope to provide a deeper insight into what may happen to anomalous returns—and "smart beta" indices—in the future.

Disappearance

"Tell me why? I don't like Mondays." – Bob Geldof, The Boomtown Rats

In 1973, Frank Cross' paper was the first published research to document the difference in returns between Fridays and Mondays. His research showed that the distribution of positive (negative) returns on Mondays preceded by positive (negative) returns on Fridays differed significantly from the corresponding daily differences in returns for the rest of the week. Cross also provided evidence that the difference in the probability of positive returns on Fridays (62%) and Mondays (39.5%) was statistically significant.[7] Taken together, these results highlighted an example of non-random movement in stock prices, therefore raising questions about the validity of the Efficient Market Hypothesis (EMH). Given the prominence of EMH at this time, the weekend effect became one of the hallmark anomalies of the period.

Whilst 1973 is viewed as the birth of literature on what is now called the "Weekend Effect," it was Kenneth French who coined the term in his 1980 paper supporting Cross' findings. In many cases, the unexpected returns were explained with recourse to a behavioral observation: companies tended to release bad news after the market's close on Fridays, and market participants did not fully account for this phenomenon in their day-to-day trading. However, following a period when many further, supportive papers were published, there began a growing movement against the initial literature.

Connolly (1989) argued that the whole effect disappeared after the 1970s, while Rogalski (1984) asserted that the anomaly could be entirely attributed to the period between Friday's close and Monday's open, and that Monday's returns from open to close did not differ significantly from those on Friday. More recently, Brusa, Liu, and Schulman (2000) showed the existence of a *reverse* weekend effect, whereas Sullivan, Timmerman, and White (2001) are skeptical that the historical results are not examples of data mining. The latest development appears to draw upon the short-selling theory to explain this violation of the EMH.[8]

To determine the impact of all this research, it is convenient to examine investment strategies based on their results. Exploiting the Weekend Effect is simple: buy stocks at the market close on Monday, and sell them at the close on the subsequent Friday. The cumulative returns attributed to this strategy as hypothetically applied to the S&P 500®, compared to the S&P 500 itself, are shown in Exhibit 1.

The log scale of Exhibit 1 allows us to observe the growth rate of cumulative returns. Until the early 1970s, the strategy's returns increased at a fairly constant rate, which appears to be reduced after this period; there appears to have been a change in the pattern of excess returns.[9]

This change is better illustrated when looking at the difference in average daily returns between the strategy and the market, i.e. the difference between the average return of the S&P 500 on Tuesdays, Wednesdays, Thursdays, and Fridays, and the average return on all five days of the trading week including Monday. As Exhibit 2 shows, a downward trend clearly started in the early 1970s, with the exception of the late 1980s, and a reverse in the downward trend emerges around 2000.

If the research confirming the anomaly's existence was convincing enough at the time, we might suppose late 1970s investors frequently sold stocks late on Fridays and bought them back on Mondays to capture the *ex-ante* returns. The expected consequence is that the more investors exploit the Weekend Effect, the worse the performance on Fridays would be, the better the performance on Mondays would be, and the lower the returns would be for such investors going forward.

This is exactly what we see in Exhibit 2; the downward trend starting in 1974 came one year after Cross' paper. The sharp increase in the difference just after 1984 coincides with Rogalski's paper questioning the Weekend Effect—and if Rogalski's paper dissuaded investors from avoiding Mondays, it takes little imagination to suppose that the "Black Monday" of October 1987 provided grounds to reconsider. A positive trend emerged

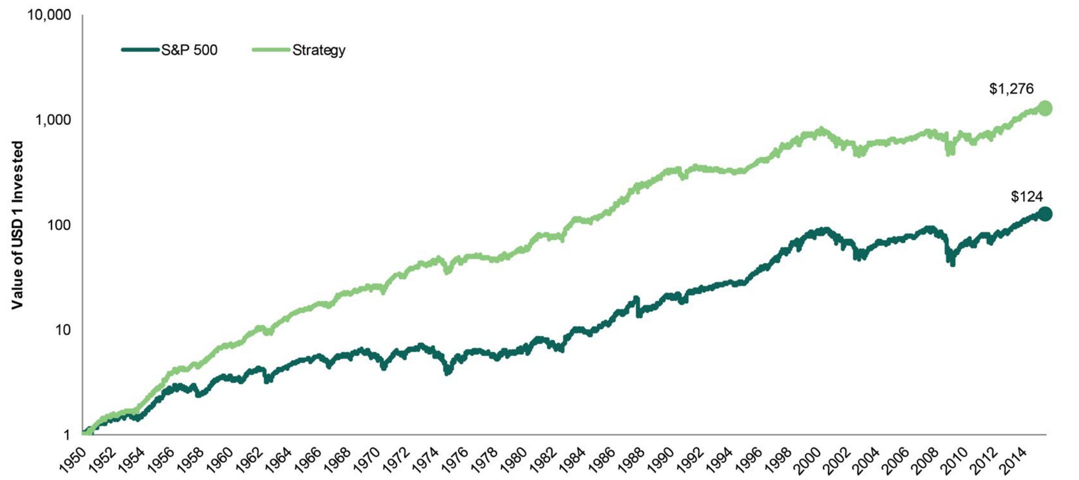

Exhibit 1: Exploiting the Weekend Effect in U.S. Equities
Source: S&P Dow Jones Indices LLC. Data from December 1949 to June 2015.
Past performance is no guarantee of future results. Chart is provided for illustrative purposes and reflects hypothetical historical performance. Please see the Performance Disclosures at the end of this document for more information regarding the inherent limitations associated with back-tested performance.

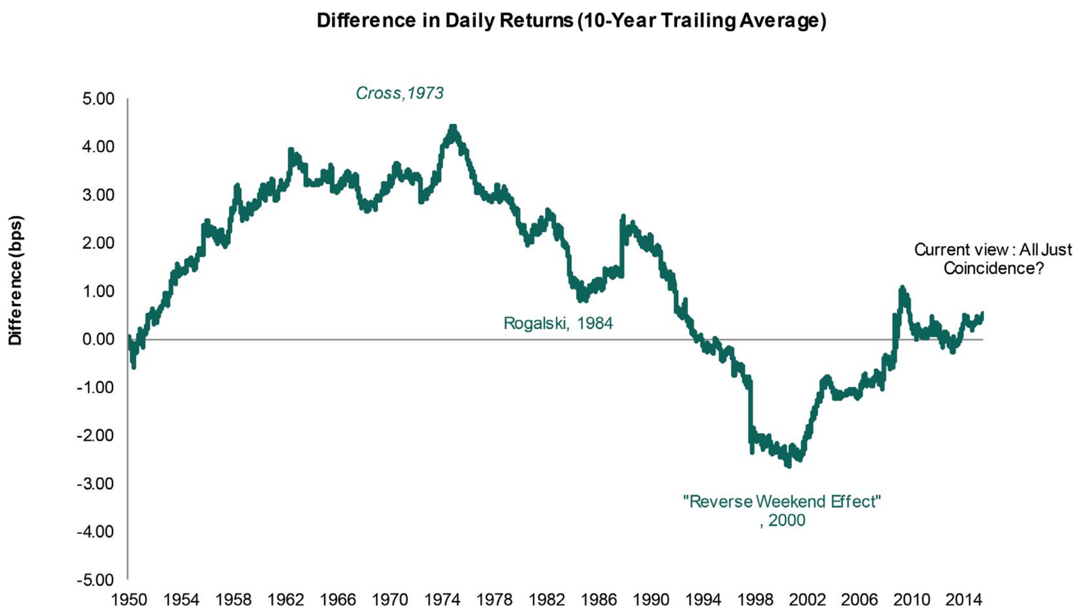

Exhibit 2: What a Difference a Day Makes
Source: S&P Dow Jones Indices LLC.
Data from December 1949 to June 2015. Line represents difference in performance between the average return of the S&P 500 on Tuesdays, Wednesday, Thursdays, and Fridays and the average return on all five days of the trading week including Monday. Past performance is no guarantee of future results. Chart is provided for illustrative purposes.

around 2000, during which there was growing skepticism about the statistical techniques used in previous research.[10] Brusa, Liu, and Schulman (2000) also published evidence in favor of a reverse Weekend Effect. Hence, the inflection points and overriding trend in the data appear to be explained by the stance of prominent research papers of the time.

As a result, the Weekend Effect exemplifies the disappearing anomaly; the pattern of returns is impacted as expected, and the returns themselves are arbitraged away as investors become aware of the anomaly's existence. The strategy itself is also easy to understand and act upon without suffering undue trading costs (using futures, for example); a characteristic that most certainly accelerated its disappearance.

Statistical Anomalies

"Get your facts first, then you can distort them as you please."
– Mark Twain

We have assumed so far that anomalies, and their disappearance, can be explained by some coherent economic or behavioral argument. In the case of the Weekend Effect, a behavioral argument involving the timing of bad news created the anomaly, and arbitrageurs' responses diminished it. But is this always a valid assumption?

The quantity of information at our fingertips today is without historical precedent. Coupled with advances in computer processing power, these data enable investors to fit many relationships within financial markets that, they believe, will provide some competitive edge. Unsurprisingly, a large number of relationships have been identified and many strategies continue to be proposed in order to obtain anomalous returns. It is possible, however, that the people proposing these investment ideas are, knowingly or otherwise, distorting the facts. In particular, what if there is no explainable pattern in returns because the returns only ever existed due to chance?

Competing with the Dutch tulip market for historical infamy, the stock market crash of the 1720s has become known as the "South Sea Bubble." After the British South Sea Company made extravagant claims about the potential value of trade deals with the New World, investors readily bought stock. But after the company's share price increased tenfold during 1720, many began selling. This downward pressure caused prices to fall, which created a liquidity crisis as leveraged investors faced margin calls. Individuals were left bewildered by the stock's wild gyrations; one of the numerous people to be left out of pocket, Isaac Newton, commented after the crash, "I can calculate the motion of heavenly bodies, but not the madness of people."

In 1992, David Dolos began to use the daily price records of South Sea Company stock to generate extraordinary profits trading the Dow Jones Industrial Average. His trading rule was simple: starting in December 1992 (for the Dow®) and starting with the South Sea Company's stock price as of August 11, 1719, if the South Sea Company's daily price increased (decreased), Dolos bought (sold short) the Dow. The next month, his position in the Dow was determined by the next day's return from the South Sea Company. Exhibit 3 shows the cumulative returns from this strategy through the end of March 2008.[11]

The strategy performed admirably, delivering triple the Dow's increase over the period. Since Dolos' discovery was not widely publicized, it is unsurprising that the anomaly persisted; if arbitrageurs were unaware of the relationship then their behavior could not have diminished it. Consequently, using such a strong predicative indicator should have made Dolos a rich man, especially during 2008-2009, when relatively few investors were able to avoid the effects of the global financial crisis. As Exhibit 4 shows, however, Dolos had no such luck.

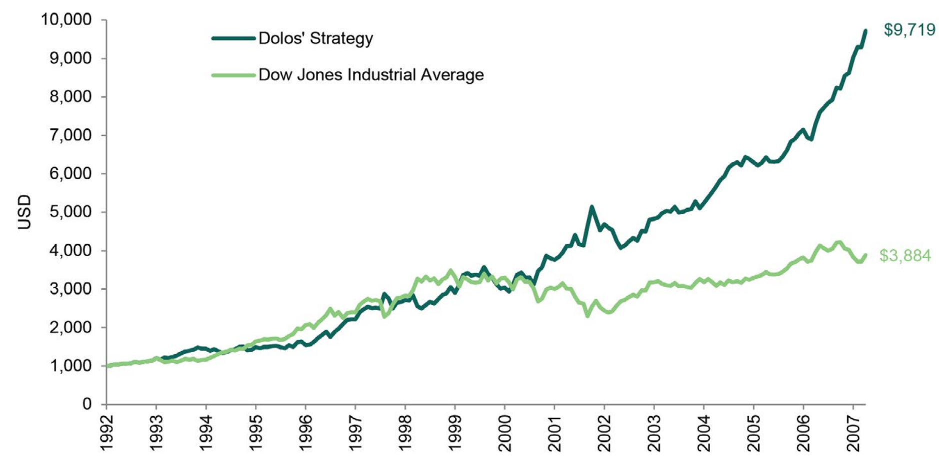

Exhibit 3: Dolos' South Sea Strategy
Source: S&P Dow Jones Indices LLC.
Data from December 1992 to March 2008. Past performance is no guarantee of future results. Chart is provided for illustrative purposes.

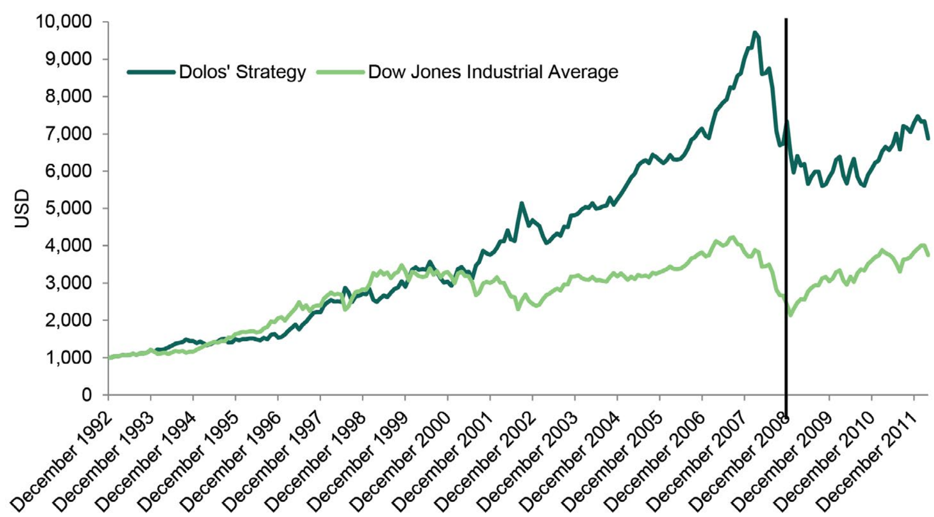

Exhibit 4: Dolos' South Sea Strategy Unravels
Source: S&P Dow Jones Indices LLC.
Data from December 1992 to December 2011. Past performance is no guarantee of future results. Chart is provided for illustrative purposes.

The strategy's cumulative returns fell dramatically after 2007, reflecting a breakdown in the predictive relationship. So what changed to influence this trend? The answer is: nothing!

David Dolos never discovered, traded, or wrote about this strategy; in fact, David Dolos never existed at all. (Scholars of Greek mythology may recall that Dolos is the spirit of trickery and guile.) The purpose of this trickery was to show how easy it can be to "mine" data using large datasets; by assigning 1s and 0s to prices that went up or down, respectively, it is straightforward to find a match using the power of computer processing. The relationship broke down because there was no more reason for its existence in the first place than coincidence—some string of 1s and 0s will yield the longest match, and it just so happens that this match has been shown on the graph between December 1992 and March 2008.

Another way to view the chance aspect of this type of anomaly is through statistics. As John Allen Paulos pointed out, "uncertainty is the only certainty there is."[12] Relatedly, the discovery of an anomaly via the use of statistical techniques is accompanied by a confidence level. This confidence level provides an indication of how likely it is that the relationship found may have arisen by chance, simply through random variations in the data.

Confidence intervals are powerful tools for isolated tests, but they are increasingly meaningless as the search broadens, a fact that means that the risk of statistical anomalies is frequently underestimated. For example, suppose an investment is proposed exploiting the predictive power of an accounting statistic—revenue per salesperson, for example. The proposer states that he has identified a profitable relationship with share prices and tells you, with a 95% degree of confidence, that the relationship has not arisen through chance alone. Dangerously, the proposer also looked at 100 different accounting statistics before finding one that worked. However, if the 95% confidence interval is correct, then by chance alone one might expect to find relationships for 5 of the 100 accounting statistics with similarly strong—yet entirely misplaced—confidence. In such circumstances, the high confidence interval provides scant comfort; if there were only one relationship found at that level of confidence, it would seem much more likely to be casual than causal. Combined with the real-world truth that researchers have tested the predictive power of thousands of statistics in manifold combinations, we should be exceedingly cautious of those few showing sufficiently convincing performance to merit inclusion in a sales pitch.

The statistical anomaly category acts as a note of caution to investors. Worse, its appearance is not limited to pure coincidence; how do you distinguish between a strong relationship and weak relationship when the weak relationship benefits from recent good fortune? There is no silver bullet to distinguish meaningful from meaningless coincidences, but there is an armory of more prosaic weapons.[13] Two types of analysis are particularly useful; the first is to extend samples beyond the time frame (or assets) in which the relationship was found. Second, and arguably more important, is a robust and critical examination of the economic reasoning behind relationships. If possible, the reasoning should be tested in other ways; for example if for U.S. stocks a high revenue per salesperson in one quarter predicts an increase in share prices the next, does the same hold in each sector? Does it work for smaller stocks and larger stocks? Does it work for Canadian companies? What happens during and after mergers of companies with differing statistics?

Nonetheless, it remains difficult to distinguish the merit of newly found strategies with sparse history, or when the proposed explanations are conceptually challenging.

Attenuation

"Every side of a coin has another side." – Myron Scholes

Risk and return in financial markets are two sides of the same coin—investors should be extremely wary of considering one without the other. Our analysis thus far has focused only on the return side of the coin, since the disappearance of arbitrageable or chance returns does not warrant an analysis of risk. Some observed effects, however, are *attenuated* by greater awareness. Our attenuation category includes anomalies which can, in principle, be impacted by increasing awareness, but where the impact is to increase the associated risk (or otherwise to adjust the balance of risk and reward). If the returns are simply a reward for risk, this is obviously grounds to expect their persistence, an explanation for why they are unlikely to be arbitraged away, and a reason for caution in investment.

In order to provide an example of an attenuated anomaly, we turn to momentum. There is a stark simplicity to the concept of trend-following and—as an informal heuristic to capital allocation—it is probably as old as commerce itself. Momentum was first formalized into a systematic investment strategy no later than the late 19th century, as a part of Dow Theory. At least as early as the 1930s, the question of its effectiveness was the subject of celebrated academic pursuits.[14] The history of momentum is rich in controversy and characters, with the post-war development of both modern financial theory and computing power, a stream of papers debated its existence and potential genesis.[15] However, the field was stacked with oddballs and fans of esoteric technical analysis; it took a different approach to bring momentum to wider prominence.

The most influential paper in the field is arguably Mark Carhart's 1997 study, which showed that adding a momentum factor to the Fama-French three-factor model considerably increased the model's explanatory power.[16] With momentum understood as a key factor in describing *cross-sectional* returns, the returns to that factor began to be broadly incorporated into risk management and active management processes; a multitude of investors took notice of its performance. Momentum has a complicated interaction with its own popularity. In the case of the Weekend Effect, its systematic exploitation acted to diminish returns, but in the case of momentum, greater awareness is initially self-reinforcing: the greater the demand for winners, the more they should continue winning. We argue that this feedback loop may give rise to a systematic instability, with continued outperformance leading to a risk of increasingly material drawdowns.

To examine the performance of momentum, the natural starting place is the so-called 12-month-1-month momentum strategy (12M-1M). It forms the basis of Carhart's extension of the Fama-French three-factor model and has since become the default expression of momentum's performance in the investment community more generally. It is also a simple strategy: as first documented in Jegadeesh and Titman's 1993 paper, the 12M-1M momentum of a security is simply its 11-month return up to one month ago. Practically, it can be viewed as an 11-month momentum strategy executed with a one-month delay.

Another justification for using 12M-1M momentum is that its prominence has resulted in the wide availability of long-term data for analysis. Exhibit 5 shows one such example, the hypothetical performance of a momentum strategy based on U.S. equities going back to 1947.[17] The performance shown in Exhibit 5 is constructed as follows: calculated monthly, the return of the momentum strategy is the difference in performance between two hypothetical portfolios, each constructed from a broad universe of listed U.S. stocks. The first portfolio comprises stocks with momentum in the top tertile among all stocks, the second portfolio comprises stocks in the bottom tertile, and the weight of each stock in each portfolio is calibrated so that neither company size nor book-to-market value differs significantly between the two hypothetical portfolios.[18] Thus, the performance of the strategy approximates those returns to momentum that are not generated by an unintended bias for cheap or smaller stocks.

As Exhibit 5 shows, between 1944 and 2015, there was a definite upward trend in the cumulative returns attributed to the momentum factor. The near straight-line performance of the strategy from 1943 to the end of the century implies a consistent growth rate more or less unvaried over decades. There appears to be some change in the pattern of returns beginning in the late 1990s, which coincides (among other things) with Carhart's influential 1997 paper, but the upward trend remains. Indeed, if we discount the performance during the 2008-2009 financial crisis, an outlier event, the returns attributed to momentum are more or less persistent. In summary, advertisement of the strong performance of the 12M-1M strategy seems to have had little impact on its returns.

But the pattern of returns *did* change. The graph in Exhibit 5 clearly becomes more volatile after the late 1990s; successes come at an increased cost. As noted in the start of this section, momentum strategies can be initially self-reinforcing. Stocks with strong price performance are bought by momentum followers, which drives up prices further and subsequently provides momentum with an even more compelling track record and more followers. As long as this continues without correction, bubbles

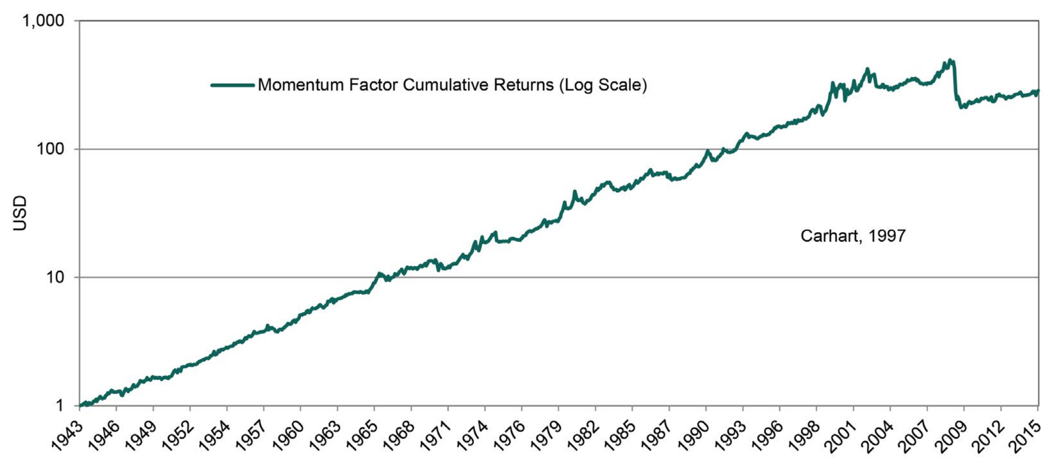

Exhibit 5: The Momentum of Momentum
Source: S&P Dow Jones Indices LLC. Data from December 1943 to June 2015.
Line shows cumulative hypothetical return of difference between high and low momentum portfolios. Past performance is no guarantee of future results. Chart is provided for illustrative purposes and reflects hypothetical (back-tested) historical performance. Back-tested data is subject to inherent limitations because it reflects application of a methodology in hindsight.

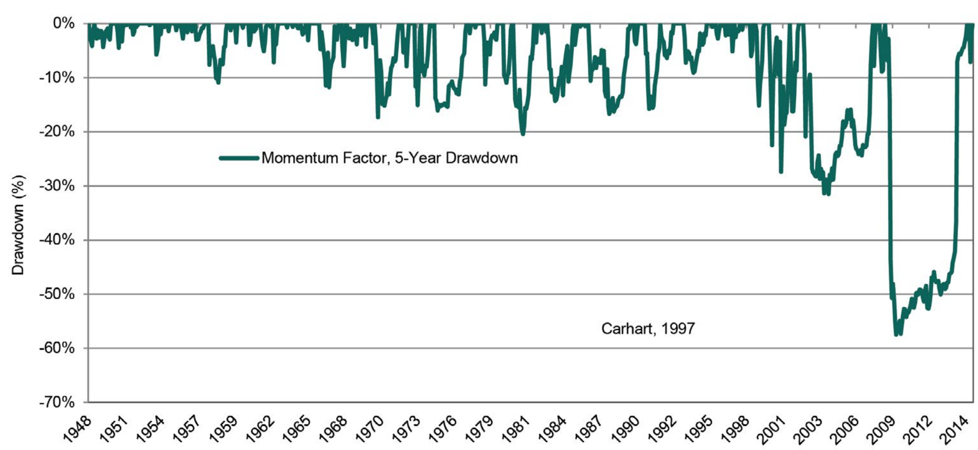

Exhibit 6: Increasing Drawdowns Over Time in Momentum
Source: S&P Dow Jones Indices LLC. Data from 1948 to 2014.
Past performance is no guarantee of future results. Chart is provided for illustrative purposes.

in the valuations of single equities are likely to form and become exaggerated. But even the most committed follower of momentum has a modicum of historical awareness, and experience tells us that *at some point*, stock valuations become so excessive that reality bites. Previous winners will become viewed as the most overpriced; a downturn hurts those stocks with positive momentum harder. As winners become losers, momentum chasers rush to sell. Those investors who wait a month to reassess their positions are hit harder still. Experience therefore suggests that as momentum strategies become increasingly popular, their propensity to generate losses during market corrections should increase.

Exhibit 6 demonstrates the increasing drawdown risks faced by the 12M-1M strategy. Specifically, the exhibit compares the cumulative return of the strategy at any point to its highest level over the previous five years, a measure of the hypothetical losses faced at the time by an investor who entered at the recent "top".

Exhibit 6 shows that while the 12M-1M momentum strategy may have continued to add returns, its downside risk has increased, especially since 1997. Carhart's paper seems relevant because such a widely read piece of research is likely to have increased the awareness and popularity of momentum strategies; certainly its publication marks a period of dramatically increased drawdowns. On a longer time scale it would appear that in fact the downside risk in momentum has been increasing since the end of WWII.

In conclusion, 12M-1M momentum epitomizes the existence of strategies for which research and popularity have not—as yet—triggered a disappearance of returns. On the surface, such persistence would appear attractive. However, the returns have come at an increasing risk, with the current risk profile appearing more elevated than ever. It may well be that the risk attributable to momentum strategies normalizes in the future, with the additional return attributable to momentum varying commensurately with the (informed) risk preferences of market participants. Or, the risk may continue to increase until its realization convinces a wide audience (including academics) to demote 12M-1M momentum from its current position as a celebrated anomaly. In either case, this risk-based attenuation of anomalous returns is conceptually possible for a majority of popular strategies, and analyzing the risk-adjusted returns attributable to strategies becomes a vital component of their assessment.

Persistence

"No matter how beautiful the theory, one irritating fact can dismiss the entire formulism, so it has to be proven" – Michio Kaku.

Some of the most elegant financial theories are also those with results that can be digested easily and have significant ramifications for investors' behavior. In our attempts to identify anomalies that can, in principle, be affected by popularity but which show return persistence without an increase in downside risk, it seems reasonable to consider an anomaly with a fairly stable risk profile.[19]

The idea that investments should offer returns commensurate to their risk, as put forward by the CAPM, is one of the cornerstones of financial theory. However, the irritating fact that contradicts this theory is the low-volatility anomaly. It was first discovered by Haugen and Heins in 1975, when they found that stocks with lower volatility in monthly returns experienced greater average returns than for the high-volatility stocks.

Rather than this discovery standing alone against a bank of literature questioning Haugen and Heins, many other papers have supported the initial findings. Similar to Haugen and Baker's (1991) work, Jagannathan and Ma (2003) showed that investing in a minimum variance portfolio delivered higher returns and lower risk in the U.S. than for the cap-weighted benchmark. In global markets, Carvalho, Xiao, and Moulon (2012) found the highest Sharpe ratio of many investment strategies was a minimum variance portfolio, while Blitz and van Vliet (2007) found a 12% spread between low- and high-volatility decile portfolios, even after accounting for value and momentum effects. More recently, various authors have shown that such anomalous effects appear to be present in most equity markets, globally.[20]

With broad evidence of a low-volatility anomaly in different markets and timeframes, and cogent behavioral and economic arguments available in support, it seems there is more than a spurious relationship at work. However, there has been growing demand for low-volatility strategies after the financial crisis of 2008, while easily accessible vehicles such as ETFs have removed barriers to constructing portfolios exploiting the anomaly and popularized the concept. The increasing awareness and popularity of low-volatility strategies leads us to wonder if the return patterns for strategies based on this anomaly have been affected—by either increased risk or diminished return.

However, if we look at the cumulative returns to the S&P 500 Low Volatility Index—either since its launch in 2011 or to the full extent of its back-tested performance since 1990, this is not the case.[21] Exhibits 7 and 8 demonstrate this persistence—first by a direct comparison of total return and, second, by comparing the risk-adjusted excess return of the S&P 500 Low Volatility Index to that of the benchmark S&P 500.

Exhibit 7 demonstrates the persistence of an excess return, but it requires us to check that such persistence has not come at the expense of increased risk. It's appropriate to evaluate the strategy's risk on a relative basis (i.e., in comparison to a market benchmark) and over a suitably long period to capture longer-term trends.[22] The risk-adjusted relative return shown in Exhibit 8 is calculated as follows: at each point in time, the previous six-year daily volatility of returns for both the S&P 500 Low Volatility Index and the S&P 500 are calculated, and the six-year total return of the S&P 500 is multiplied by the ratio of the two volatilities to derive a "risk-adjusted benchmark return." The risk-adjusted benchmark return is thus the return of the S&P 500, but scaled to the volatility of the low-volatility strategy. The risk-adjusted *relative* return is the six-year return of the S&P 500 Low Volatility Index, minus the risk-adjusted benchmark return. Thus, the risk-adjusted relative return is the excess (or deficit) return in the strategy compared to the volatility-scaled benchmark's return. If the risk-adjusted relative return is greater than zero, we appear to be earning a greater return than might be expected given the strategy's risk, and vice-versa. The results are shown in Exhibit 8.

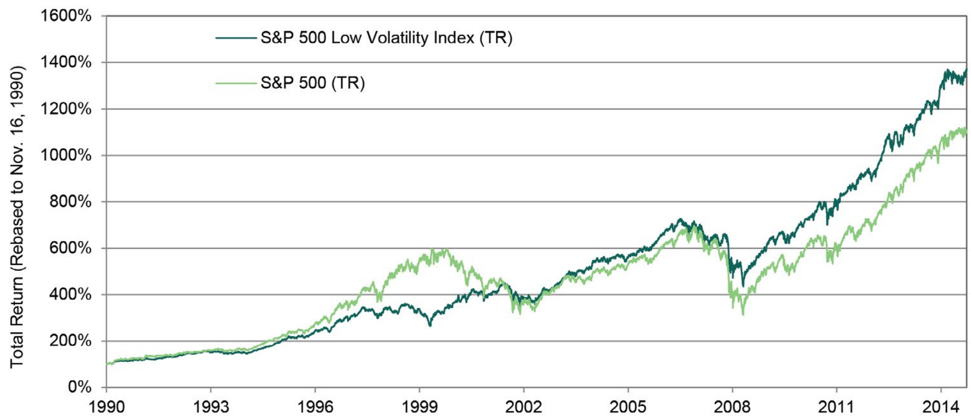

Exhibit 7: S&P 500 Low Volatility Index Outperformance
Source: S&P Dow Jones Indices LLC.
Data from November 1990 to August 2015. Past performance is no guarantee of future results. Chart is provided for illustrative purposes. Some data for the S&P 500 Low Volatility Index reflect hypothetical historical performance. Please see the Performance Disclosures at the end of this document for more information regarding the inherent limitations associated with back-tested performance.

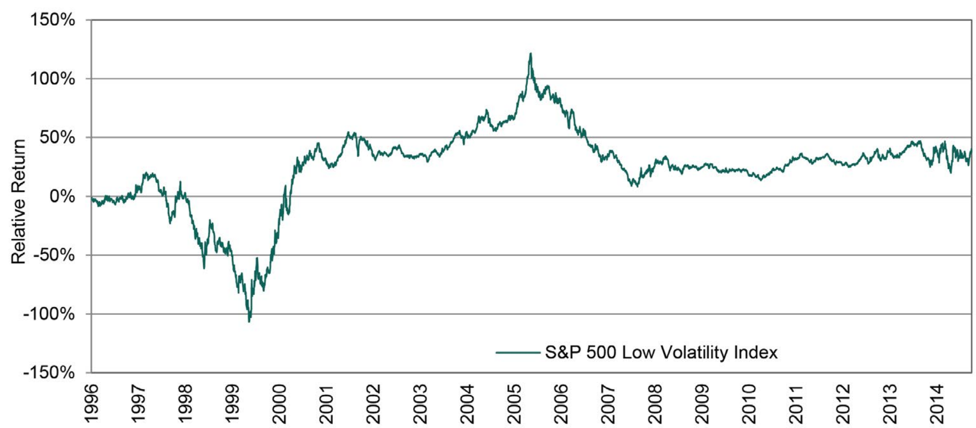

Exhibit 8: S&P 500 Low Volatility Index Six-Year, Risk-Adjusted Relative Return
Source: S&P Dow Jones Indices LLC. Data from 1990 to 2014.
Past performance is no guarantee of future results. Chart is provided for illustrative purposes and reflects hypothetical historical performance. Please see the Performance Disclosures at the end of this document for more information regarding the inherent limitations associated with back-tested performance.

Aside from two periods around 2000 and 2008, the pattern of risk-adjusted annual returns remains relatively flat; the oscillations persist around a stable, positive mean. If anything, notwithstanding those two major events, the level of the long-term, risk-adjusted relative returns would appear to be *increasing* over time. In particular, the current reading (covering the years since the market for U.S. equities began its remarkable bull run) is as good as, if not better than, what might be expected from history and current circumstances.

The S&P 500 Low Volatility Index provides a particularly resonant example of persistent anomalous returns that are not easily dismissed as a compensation for risk. However, a note of caution is still needed. All that Exhibits 7 and 8 demonstrate conclusively is that, *so far,* the investment and attention directed toward low-volatility strategies has not been sufficient to temper their returns or attenuate their risk/return profile. This can be taken as an indication that, whatever investment flows or perspectives give rise to the anomaly, they exceed those set to exploit it—by several orders of magnitude. As such, this analysis may provide a degree of comfort to investors considering such strategies.

Conclusion

"In theory, there is no difference between theory and practice. In practice, there is." – Yogi Berra

Some might see our attempts to categorize anomalies as a fact-finding mission that has little practical benefit or a zoo-like menagerie of some things that have happened to some anomalies and may happen to others, but this would miss the bigger point. In particular, we stress that investors should be wary of analyzing returns in isolation without any consideration for the associated risk, and that seemingly persistent returns may actually be a reward for thus far *unappreciated* risks**.**

More important, arguably, is an awareness of the chance relationships in large datasets; the power of computers means that an increasing number of these relationships can be found at an exponentially increasing risk of confusing the spurious with the causal. Moreover, the sophisticated explanations proposed for some statistical anomalies can make this effect fiendishly difficult to identify and avoid. To reduce the possible impact of unanticipated changes in the returns' patterns, solutions such as extending samples and thinking about the economic reasoning are on offer.

It would be naïve to expect persistent performance from anomalies that rely on investors behaving insensibly, are easy to trade, and that are not a reward for risk—unless evidence suggests that the bank of investors offering to be exploited is deep pocketed and broadly populated. Examining the performance of strategies as they are popularized by broadly cited academic papers and offered in products made widely available allows us to glean information about what is driving their unexpected returns, and the potential for those returns either to continue or to come at the price of increased risk. This provides a toolkit to use when assessing the success of many strategies.

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Endnotes

1. Asness, Cliff, "How Can a Strategy Still Work If Everyone Knows About It?" Aug. 31, 2015.
2. Fama, Eugene F. and Kenneth R. French, "The Cross-Section of Expected Stock Returns," The Journal of Finance, June 1992.
3. Asness (op. cit.) argues that the anomalies come about "because investors make errors."
4. See BlackRock Global ETP Landscape, December 2014, p. 4. "Organic growth for smart beta is 18%, twice that of market-cap weighted equity ETPs."
5. The authors acknowledge their debt in particular to two papers that inspired their approach, namely Harvey et al "… and the Cross Section of Expected Returns" (2015) and McLean & Pontiff, "Does Academic Research Destroy Stock Return Predictability?" (forthcoming).
6. To clarify, disappearing anomalies really do exist, for a while, until they become widely appreciated, at which point they vanish. Statistical anomalies, in the sense used here, are mirages—there's really nothing there, and never was—although with enough data mining, an effect may appear to be real.
7. The results given in Cross' paper are for the S&P Composite 1500® between Jan. 2, 1953, and Dec. 21, 1970. Similar results were found for the Dow Jones Industrial Average® and the New York Stock Exchange Composite Index, but these were not included in the paper.
8. See Chen and Singal (2003).
9. The fact that the October 1987 crash occurred on a Monday might cause concern over the dominance of extreme events in such results. In fact, once removing extremes from the data, both the original Weekend Effect and its disappearance during the 1980s remain evident.
10. See Sullivan, Timmerman, and White (2001) for a more detailed discussion on the critiques of statistical techniques used to derive evidence in favor of the Weekend Effect.
11. South Sea daily returns are those between Aug. 11, 1719, and June 29, 1720 (source: International Center for Finance at Yale). The monthly returns on the DJIA are those between Dec. 31, 1992, and March 31, 2008.
12. See Paulos, John Allen, A Mathematician Plays the Stock Market, 2003.
13. See Lazzara, Craig J., "The Limits of History," January 2013.

14. See Cowles (1933)
15. See Swinkels (2003) for an overview.
16. Carhart, Mark M., "On Persistence in Mutual Fund Performance." The paper has 8,985 citations on Google Scholar, as of Aug. 18, 2015, which ranks highest for all the research papers on momentum we analyzed. See also Fama and French, op. cit.
17. In fact, performance is available going back to 1924; we exclude the pre-war period in part acknowledgement of the very different market environment of the time, but the reader may be interested to know that the market crash of 1929 represented a reversal in momentum's performance far greater than any seen since.
18. Full details on the construction of the momentum factor, as well as a downloadable return series, are available in the French Factor Library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library.html.
19. The result was anticipated by the observation that market beta appeared to be negatively correlated to returns, found in Black, Jensen, and Scholes' earlier 1972 paper; "The Capital Asset Pricing Model: Some Empirical Tests."
20. This spread was found using data between 1986 and 2006 and the paper provides potential explanations for the existence of the anomaly: leverage-confined investors being unable to arbitrage away the returns; inefficient decentralized investment approaches; and behavioral biases among private investors. See also Chan, Fei Mei and Craig J. Lazzara, "Is the Low Volatility Anomaly Universal?" April 2015.
21. The S&P 500 Low Volatility Index comprises 100 stocks that are members of the S&P 500 and have the lowest levels of realized volatility over the previous 12 months. Rebalancing occurs quarterly, with the index weights of each component set at each rebalance in inverse proportion to realized volatility.
22. We chose six years so that the most recent values capture the strong bull market in equities that began in March 2009 and encompass the period over which low-volatility may be said to have gained its current popularity, but the results are not particularly sensitive to the length of period chosen.

About S&P Dow Jones Indices

S&P Dow Jones Indices LLC, a part of McGraw Hill Financial, Inc., is the world's largest, global resource for index-based concepts, data and research. Home to iconic financial market indicators, such as the S&P 500® and the Dow Jones Industrial Average™, S&P Dow Jones Indices LLC has over 115 years of experience constructing innovative and transparent solutions that fulfill the needs of institutional and retail investors. More assets are invested in products based upon our indices than any other provider in the world. With over 1,000,000 indices covering a wide range of assets classes across the globe, S&P Dow Jones Indices LLC defines the way investors measure and trade the markets. To learn more about our company, please visit www.spdji.com.

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New Evidence on Whether Gold Mining Stocks Are More Like Gold or Like Stocks

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Introduction

The role of gold as an investment asset is a longstanding question of scholars and practitioners of portfolio management. Large changes in stock prices and gold prices in the past two decades have heightened this interest. An ancillary question related to the role of gold in an investment portfolio is the role of gold mining stocks. Are gold mining stocks actually part of the stock component of a portfolio, or are they just another way to hold gold? This is the question that we will answer. There is an existing literature, though not particularly large, that addresses the question posed. We see reasons to address this question once more. One reason is that the worldwide financial crisis and recession in 2007-2009 caused a large increase in the price of gold, and a large decrease in stock prices. Then, as the recession faded, these prices reversed direction. Large changes like this allow the opportunity to observe the relationship between stock prices and gold prices when it likely matters most: when large price changes occur.

Also, exchange traded funds (ETFs) for gold, gold mining stocks, and a variety of stock portfolios have become available. As investable assets, ETFs provide a realistic picture of actual assets investors now use in practice, and are more likely to be used in the future. Because of this we use ETFs as our source of data. The use of recent data that encompasses the period before, during, and after the financial crisis and recession, combined with the use of ETF data, constructively advances the existing literature.

The paper is structured as follows. In section two, we review the related literature. This is followed in section three with a description and discussion of the data. Regression models to examine the relationship between gold mining stocks, gold, and stocks are presented in section four. Section five summarizes and examines what our results imply for portfolio management.

The Related Literature

There is a fairly large literature on gold as an investment asset. We are concerned with the return characteristics of gold mining stocks, not gold per se. This narrows considerably what we consider to be the relevant literature. Our empirical work is most similar to Tufano (1998). He estimated market model regressions in which the return on gold mining stocks was the dependent variable, and the return on gold, and the return on the stock market (the Center for Research in Security Prices NYSE/AMEX/Nasdaq composite value weighted index) were the explanatory variables. With data from January 1990 through March 1994, he estimated models with daily, weekly, and monthly data for 48 individual North American gold mining firms. His results using the traditional estimation procedure show that the mean betas on the gold return variable were 1.03, 1.41, and 1.88 for daily, weekly, and monthly data. The mean betas on the stock market return variable were -0.05, 0.27, and 0.48. Thus, it appears that gold mining stocks are far more sensitive to gold returns than they are to stock market returns. In other words, gold mining stocks are more like gold than like stocks. Moreover, the traditional betas on the stock market return variable are all well below one, with the daily return beta negative. Gold mining stocks with their low betas with the stock market would have a risk-reducing impact on the systematic risk of an overall stock portfolio. We note that the daily, weekly, and monthly betas differ in a non-trivial way. The phenomenon of betas varying with the period of return data warrants attention because choice of using only one return frequency (e.g., monthly) to estimate "the beta" may not be appropriate in light of the differences in beta estimates one can observe with different return frequencies.

We extend the approach used by Tufano to estimate beta values for gold mining stocks that differentiate beta values during bull and bear periods. We also assess whether gold and gold mining stocks are a hedge, diversifier, or safe haven. These three terms are defined in Baur and Lucey (2010). A hedge is an asset that, on average, is negatively correlated with a portfolio. A diversifier, on average, is positively, but not perfectly correlated, with a portfolio. A safe haven is uncorrelated or negatively correlated with a portfolio during times of market stress.

The other related literature is not concerned directly with whether gold mining stocks are more like gold or more like stocks. Instead, the concern is more with whether adding gold or adding gold mining stocks to a portfolio is preferred. In a sense, this is a related question. If gold stocks are more like stocks, then they will add little diversification benefits compared to adding gold. If gold mining stocks are more like gold, then they provide similar diversification benefits as gold and can serve as a substitute for gold. Moreover, if the returns on gold mining stocks exceed that of gold (but with similar correlation with stocks and similar standalone variability), then gold mining stocks would be preferred to gold. Knowing which situation is the case, of course, is important to actual portfolio management decisions.

Jaffe (1989) examined data from 1971 through June 1987. He used an index of gold stocks traded on the Toronto Stock Exchange, the return on gold bullion, and other financial assets (all measured in U.S. dollars). During this period, the mean return on gold mining stocks was 2.16%. This exceeded the return on gold of 1.56%, and the return on the S&P 500 of 1.06%. The correlation coefficients between these three assets were: gold and gold mining stocks 0.645, gold and stocks 0.054, and stocks and gold mining stocks 0.304. From a risk reduction perspective the lowest correlation, between gold and stock, suggests that adding gold to a stock portfolio is preferred to adding gold stocks. The higher gold mining stock return as compared to the gold return, however, implies a tradeoff because gold mining stocks provide more return enhancement than gold. Jaffee shows that adding either gold or gold stocks to an existing portfolio improves the risk-return profile of the reconfigured portfolio.

Chua, Sock, and Woodward (1990) use monthly return data on gold, gold mining stocks (the Toronto Stock Exchange Gold Index), and the stock market (the Standard and Poor's 500 Index) from September 1971 through December 1988. A basic market model with only the stock market return as the independent variable was estimated for gold and for gold mining stocks as the dependent variables. The beta for gold is 0.11, and the beta for gold mining stocks is 0.86. The corresponding correlation coefficients are 0.050 and 0.345. The gold mining stocks show a much higher sensitivity to stock market returns than to gold returns. The sample is split into September 1971 to December 1979 and January 1980 to December 1988. For gold, the beta was 0.03 in the early period and 0.22 in the latter period. The correlation coefficient was 0.011 in the early period and 0.118 in the latter period. For the gold mining stocks, the beta was 0.57 in the early period, and 1.12 in the latter period. The correlation coefficient was 0.245 in the early period, and 0.424 in the latter period. The higher latter period correlation coefficient shows diminished diversification benefits of gold mining stocks. The beta of 1.12 suggests that adding gold mining stocks to a diversified stock portfolio (with a beta equal to one) would increase the systematic risk of this portfolio. This illustrates that correlations and betas for gold and gold mining stocks are far from constant over time. Because of the latter period result for gold stocks, the authors comment (p. 79): "Our results call into question, however, the benefit of diversifying with gold stocks..."

Conover, Jensen, Johnson, and Mercer (2009) examine daily data from January 1973 through December 2006. During this time, the annualized return on gold was 6.64% (standard deviation 20.90%). For gold stocks this was 11.22% (standard deviation 26.79%). U.S. stocks had a return of 10.83% (standard deviation 15.37%). The correlation of gold stocks with U.S. stocks was 0.05, and the correlation of gold with U.S. stocks was -0.03. These low correlations for both assets suggest large diversification benefits from either gold or gold equities. The large return difference in favor of gold stocks versus gold leads the authors to conclude (p. 76): "The investment benefits are considerably larger if the exposure to precious metals is obtained indirectly via an investment in the equities of precious metals firms, rather than directly by purchasing the precious metal as a commodity (e.g., gold bullion)."

As shown from the above review, the existing literature is not clear on whether investors are better served by adding gold or adding gold mining stocks to an existing portfolio. The results are sensitive to the sample period used. The recent heightened interest in gold and gold mining stocks by practitioners in portfolio management provides a further reason to present an up-to-date analysis. For example, in the practitioner journal Financial

Daily data					
	Mean	σ	Min	Max	N
R_{GDX}	0.011	2.772	-15.532	26.538	2,258
R_{GLD}	0.033	1.302	-8.781	11.291	2,258
R_{SPY}	0.032	1.340	-9.845	14.520	2,258
Weekly data					
R_{GDX}	0.016	5.429	-18.923	23.418	468
R_{GLD}	0.161	2.703.	-9.220	13.805	468
R_{SPY}	0.144	2.667	-19.793	13.292	468
Monthly data					
R_{GDX}	0.036	110.74	-37.999	34.184	107
R_{GLD}	0.757	5.568	-16.140	12.787	107
R_{SPY}	0.586	4.479	-15.923	11.467	107

Exhibit 1: Summary Statistics
Source: Author's Calculations
R_{GDX} are the returns for the Market Vectors Gold Miners ETF, R_{GLD} are the returns for the SPDR Gold Shares, and R_{SPY} are the returns for the SPDR S&P 500 ETF Trust.

Planning, Day (2012) comments that gold rose sevenfold in the first five years of the recent gold bull market, while gold stocks only doubled. He offers numerous explanations for this divergence. One is the introduction of gold ETFs that track the price of gold, such as the SPDR Gold Trust. This fund has made obtaining an exposure to gold easy, and reduced the demand for using gold mining stocks as a way to obtain gold exposure. He mentions that gold stocks reflect the stock market as well as the gold price. Also, he claims that security analysts may have been too conservative in setting target prices for gold mining stocks because they have been too conservative in assumptions about the gold price used in their analyses.

Data and Summary Statistics

We examine the returns of three assets: gold, gold mining stocks, and a diversified portfolio of large capitalization U.S. stocks (the S&P 500). For each asset, we use ETFs that track the returns on the corresponding asset. ETFs are a fairly new financial market product. They allow investors to easily hold asset classes. From an academic perspective, ETFs are attractive to use in empirical research as they represent returns on investable asset classes. There is no need to create portfolios to mimic what the returns to investors might have been. The ETFs are actual portfolios that can be and are held, so the returns precisely represent relevant returns. This is particularly appealing in the case of an ETF that invests in gold mining stocks. Early analysts had to create portfolios meant to mimic possible returns to holding gold mining stocks. GDX is the ticker symbol for an ETF of gold mining stocks, Market Vectors Gold Miners ETF. The GDX ETF measures what an investor seeking exposure to gold mining stocks would earn if the exposure is from holding this ETF. The GDX ETF holds 40 gold mining stocks and the underlying index is the NYSE ARCA Gold Miners Index, a modified market-capitalization weighted index. GLD is the ticker symbol for an ETF that tracks the market price of gold, SPDR Gold Shares. SPY is the ticker symbol for an ETF that tracks a portfolio of the Standard and Poor's index of 500 stocks, SPDR S&P 500 ETF Trust. These are all assets traded in the U.S., so the analysis is from the perspective of a U.S. investor.[1]

The initial date that each ETF began trading was May 22, 2006 for GDX, November 18, 2004 for GLD, and January 29, 1993 for SPY. Therefore our period of analysis begins in May 2006. It ends in May 2015. We have 2,258 daily return observations, 468 weekly return observations, and 107 monthly return observations. Exhibit 4 shows the price evolution for GDX, GLD, and SPY over the sample period.

The price and dividend data were obtained from Yahoo! Finance. Returns were calculated for daily, weekly, and monthly data. The percentage return was calculated as:

$$R_t = [(P_t - P_{t-1} + D_t)/P_{t-1}] \times 100 \qquad (1)$$

The closing prices (daily, weekly, and monthly) for each period t are denoted as P. The dividend per share in period t is D. The stock-holding ETFs (SPY and GDX) pay dividends, whereas GLD does not. Exhibit 1 shows the summary statistics for our return series, split into the daily, weekly, and monthly return frequencies. During this sample period, gold had a higher average return than stocks, and stocks had a higher return than gold mining stocks. In terms of variability measures, the gold mining stocks had a larger standard deviation of return (roughly twice) than either gold or stocks, which had similar standard deviations. Similarly, the minimum and maximum values of return show a much wider dispersion for the gold mining stocks than for both gold and stocks. So, during this period, gold mining stocks were inferior to gold or to stocks in terms of return, and also had higher risk when measured with standard deviation.

Exhibit 2 presents the correlation of returns across the three assets. With the daily return data, the correlation of gold mining stocks with gold is 0.76, and the correlation of gold mining stocks with the stock market is 0.35. With the weekly returns these are 0.80 and 0.29. With monthly returns these are 0.83 and 0.19. Gold mining stocks are far more correlated with gold returns than with stock returns. The implication is that gold mining stocks are more like gold than like stocks. We hasten to add, however, that the gold mining stocks do have a non-trivial positive correlation with stock returns, so both gold and stocks seem to explain gold mining stock returns. Notice that the correlation of gold with the

Full Correlation Matrix

Daily data

	R_{GDX}	R_{GLD}	R_{SPY}
R_{GDX}	1.0000		
R_{GLD}	0.7604	1.0000	
R_{SPY}	0.3468	0.0603	1.0000

Weekly data

	R_{GDX}	R_{GLD}	R_{SPY}
R_{GDX}	1.0000		
R_{GLD}	0.7604	1.0000	
R_{SPY}	0.3468	0.0603	1.0000

Monthly data

	R_{GDX}	R_{GLD}	R_{SPY}
R_{GDX}	1.0000		
R_{GLD}	0.8344	1.0000	
R_{SPY}	0.1885	0.0680	1.0000

Partial correlations of RGDX with RGLD and RDGT

Daily data

	Partial Correlation
R_{GLD}	0.7899
R_{SPY}	0.4643

Weekly data

	Partial Correlation
R_{GLD}	0.8315
R_{SPY}	0.4657

Monthly data

	Partial Correlation
R_{GLD}	0.83860
R_{SPY}	0.2397

Exhibit 2: Correlation Matrices
Source: Author's Calculations
R_{GDX} are the returns for the Market Vectors Gold Miners ETF, R_{GLD} are the returns for the SPDR Gold Shares, and R_{SPY} are the returns for the SPDR S&P 500 ETF.

stock market is 0.06, 0.02, and 0.07 for daily, weekly, and monthly returns (lower than the 0.35, 0.29, and 0.19 values of gold mining stocks with the stock market). Gold mining stocks and gold are both “diversifiers” with positive but low correlation, but gold clearly is the superior diversifier, with much lower correlations with stock returns. Neither gold, nor gold mining stocks are “hedgers” because neither has a negative correlation with the stock market.

In the lower part of Exhibit 2 we show the partial correlation coefficients of the gold stock returns with the gold return and the stock market return. These partial correlations will hold constant the other variable. So for example, the partial correlation coefficient of 0.79 of gold mining stocks with gold with the daily data holds constant the influence of the stock market return on the gold mining stocks. The partial correlation coefficient of 0.46 of gold stocks with the stock market with the daily data holds constant the influence of the gold return. These and all the other partial correlations are higher than the analogous standard unconditional correlations. The simple correlations of gold mining stocks with gold, already high, are marginally higher when the partial correlation is considered. The simple correlations of gold mining stocks with the stock market, are much lower, and show larger increases in the partial correlation. This suggests a joint influence of both gold and the stock market on gold stock returns which we examine further in regression models.

Regression Models

We can now turn to the regression analyses of our data. Models 1 and 2 are simple bivariate regression models to judge the explanatory power of the stock market alone and the gold return alone in explaining gold mining stock returns (GDX).

Model 1: $R_{GDX,t} = \alpha + \beta_1 R_{SPY,t} + \varepsilon_t$ (2)

Model 2: $R_{GDX,t} = \alpha + \beta_2\, R_{GLD,t} + \varepsilon_t$ (3)

When these typical market models are estimated with only the stock market return as the explanatory variable, the beta for gold mining stocks is 0.72 for daily returns, 0.60 for weekly returns, and 0.47 for monthly returns. All are statistically significant. With all of these coefficients below one, the interpretation is that gold mining stocks are stocks have less than average risk. The adjusted R-squared values are 0.12 for daily returns, 0.08 for weekly return, and 0.03 for monthly returns. A relatively small proportion of gold mining stock return variability is explained by stock market returns.

Model 2 shows the results when only the gold return is included. This models shows much higher beta values when gold is the explanatory variable than was the case for the stock market return: 1.62 for daily returns, 1.61 for weekly returns, and 1.66 for monthly returns. All are statistically significant. Gold mining stocks respond more than proportionately to a given gold return, with the magnitude of these betas similar to those reported by Tufano (1998). The adjusted R-squared values are much higher than they were for model 1: 0.58 for daily returns, 0.64 for weekly returns, and 0.69 for monthly returns. In sum, gold mining stocks are far more responsive to gold returns than to stock market returns, and gold returns alone explain gold mining stock returns far better than do stock market returns alone.

Model 3 enters both the stock market return and the gold return as independent variables to consider them jointly.

$$\text{Model 3: } R_{GDX,t} = \alpha + \beta_3 R_{SPY,t} + \beta_4 R_{GLD,t} + \varepsilon_t \tag{4}$$

The model 3 results do not change the beta values obtained in models 1 and 2 in a substantial way. We note that both variables remain statistically significant in this expanded model. Given the model 1 and 2 results, this result was not unexpected.

Models 4 and 5 add interaction terms to models 1 and 2. In each case, the independent variable is used to create a dummy variable set equal to one if the return on the variable is positive (a "bull" period), and zero otherwise (a "bear" period). What this does is allow there to be beta coefficients during bull periods (when stock returns or gold returns are positive). This "bull beta" is the coefficient on the variable plus the coefficient on the interaction term. The "bear beta" is simply the coefficient on the non-interacted term variable. For example, with model 4, the bull beta is β5 + β6. The bear beta is simply β5. Models 5 and 6 coefficients are interpreted similarly. As before, we first look at stock market returns and gold returns separately, in models 4 and 5. Then, both variables are entered into model 6.

$$\text{Model 4: } R_{GDX,t} = \alpha + \beta_5 R_{SPY,t} + \beta_6 (R_{SPY,t} * BULL_{SPY,t}) + \varepsilon_t \tag{5}$$

$$\text{Model 5: } R_{GDX,t} = \alpha + \beta_7 R_{GLD,t} + \beta_8 (R_{GLD,t} * BULL_{GLD,t}) + \varepsilon_t \tag{6}$$

$$\text{Model 6: } R_{GDX,t} = \alpha + \beta_9 R_{SPY,t} + \beta_{10} R_{GLD,t} + \beta_{11} (R_{SPY,t} * BULL_{SPY,t}) + \beta_{12} (R_{GLD,t} * BULL_{GLD,t}) + \varepsilon_t \tag{7}$$

Model 4 results regarding differences in bull and bear stock market betas are inconclusive. Using daily data, the bull beta is 0.629 (0.801 – 0.172), and the bear beta is 0.801. The p-value for the coefficient on the interaction term, however, is 0.105, so the statistical significance is marginal. Similarly with weekly and monthly data the interaction term coefficient is statistically insignificant, implying that the beta is statistically indistinguishable in bull and bear stock markets.

Model 5, with the daily data, shows that when gold is in a bull period, gold mining stocks have a gold bull beta of 1.778 (1.471 + 0.307). This is much higher than the gold beta in bear periods of 1.471. This is an economically significant result, and also a statistically significant ($p = 0.000$) result. With the weekly and monthly data this relationship no longer exists. The coefficient on the interaction term becomes statistically zero. Thus, whether the gold beta for gold mining stocks differs in bull and bear periods hinges on the return frequency used. A difference is apparent in the daily return data, but not in the weekly or monthly data.

Model 6 subsumes models 4 and 5. The daily data results again are not consistent with the weekly and monthly data results. In this model, the bull beta for SPY is 0.453 (0.813 + (-0.360)), which is much lower than the SPY bear beta of 0.813 for the stock return variable. The significant SPY interaction term coefficient shows that this difference is statistically significant. The gold bull beta is 1.869 (1.314 + 0.555), which is much higher than the bear beta of 1.314 for the gold return variable. This also is both economically and statistically significant. With the weekly and monthly returns none of the interaction terms are statistically significant.

One might presume that the daily results are more reliable. Daily frequency data are less subject to other confounding influences that can occur as the time frame of the return measurement is expanded to weekly or monthly. If the daily return results should be given more attention for this reason, it does appear to be the case that gold mining stock sensitivities are different depending on whether the stock market returns or gold returns are positive or negative. How might the results be interpreted? Factors that lead to high stock returns include increased investor optimism, and reduced risk aversion that increases demand for stock. These factors might have a more muted impact on gold mining stocks demand even with gold price effects accounted for, creating the observed different sensitivity to bull and bear markets. A higher gold return beta for bull gold markets would be consistent with investors knowing or perceiving that some gold mining firms hedge downward moves in gold prices. Firms could purchase of put options on gold, thus mitigating somewhat the impact of declines in gold prices (e.g., see Tufano, 1996). This could create a higher bull beta than bear beta with respect to gold prices.

For completeness and comparison purposes, we also estimated a few additional models. We estimated a model analogous to model 4 in Exhibit 3, but with the GLD substituted for GDX as the dependent variable. The interacted term was never statistically significant, so we do not show complete results. Thus, the bull and bear betas for gold are statistically indistinguishable. We also considered the "safe haven" aspects of gold and gold mining stocks. A safe haven asset would have positive returns when returns for the stock market are large and negative. We chose the fifth percentile or lower return values for the daily, weekly, and monthly stock market returns. Using this criterion, the number of significant market decreases in our sample period was 113 out of 2,258 observations for the daily data, 24 out of 468 observations for the weekly data, and 6 out 107 observations for the monthly data. These observations were classified with a dummy variable which was interacted with the stock market return. The interacted term and the stock market return are the independent variables in this model (analogous to model 4 in Exhibit 3). In this case, for an asset to be a safe haven, the coefficient on the interaction term

Daily data						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
R_{SPY}	0.717 (0.000)		0.625 (0.000)	0.801 (0.000)		0.813 (0.000)
R_{GLD}		1.619 (0.000)	1.580 (0.000)		1.471 (0.000)	1.314 (0.000)
R_{SPY} * $BULL_{SPY,t}$				-0.172 (0.105)		-0.360 (0.001)
$R_{GLD,t}$ * $BULL_{GLD,t}$					0.307 (0.000)	0.555 (0.000)
Adjusted R^2	0.120	0.578	0.669	0.121	0.581	0.678
Weekly data						
R_{SPY}	0.597 (0.000)		0.569 (0.000)	0.596 (0.000)		0.558 (0.000)
R_{GLD}		1.606 (0.000)	1.597 (0.000)		1.656 (0.000)	1.566 (0.000)
R_{SPY} * $BULL_{SPY,t}$				0.001 (0.998)		0.029 (0.834)
$R_{GLD,t}$ * $BULL_{GLD,t}$					-0.102 (0.555)	0.065 (0.679)
Adjusted R^2	0.084	0.639	0.717	0.082	0.638	0.716
Monthly data						
R_{SPY}	0.466 (0.052)		0.327 (0.013)	0.398 (0.336)		0.596 (0.014)
R_{GLD}		1.660 (0.000)	1.642 (0.000)		1.596 (0.000)	1.409 (0.000)
R_{SPY} * $BULL_{SPY,t}$				1.150 (0.841)		-0.515 (0.223)
$R_{GLD,t}$ * $BULL_{GLD,t}$					0.117 (0.745)	0.444 (0.230)
Adjusted R^2	0.026	0.693	0.708	0.017	0.691	0.709

Exhibit 3: Market Vectors Gold Miners Models
Source: Author's Calculations
This Exhibit represents daily, weekly, and monthly time series regressions using the dependent variable, returns for the Market Vectors Gold Miners ETF (R_{GDX}). Statistical significance is determined by p-values provided in parentheses.

should be negative, and statistically significant, and the sum of the coefficients on the interacted term and the stock market return should be negative. Neither for gold nor for gold mining stocks do the conditions for a safe haven hold for any of the return data frequencies.

Conclusions and Implications for Portfolio Management

Are gold mining stocks are more like gold or more like stocks? They are more like gold. What do these results imply for portfolio management? Because gold mining stock returns behave far more like gold returns than like stock returns suggests that the two are substitutes in an overall portfolio. Closer scrutiny implies that this is not necessarily the case. Suppose that an investor has an existing portfolio comprised solely of stocks, none of which are gold mining stocks. If the question posed is: "Should my overall portfolio include x% in gold in addition to the stock component, or should my overall portfolio include x% in gold mining stocks in addition to the stock component, or is either choice the same?" The answer our results point to is for gold to be added. The substantially lower correlation of gold with stocks than gold mining stocks with stocks implies that gold provides superior diversification benefits. A caveat is that if the gold mining stocks provide a higher expected return than gold, this could outweigh gold's superiority as a risk-reducing asset in a portfolio when the overall risk-return profile is considered. While gold mining stocks could have higher returns than gold, as has happened in the past, in our period of analysis this was not the case. If the question posed instead is: "If my portfolio of stocks does not include gold mining stocks, and I cannot or will not hold any gold, should I add gold mining stocks?" The answer is that question is yes, gold mining stocks can provide a good, but not perfect substitute for holding gold in an overall portfolio.

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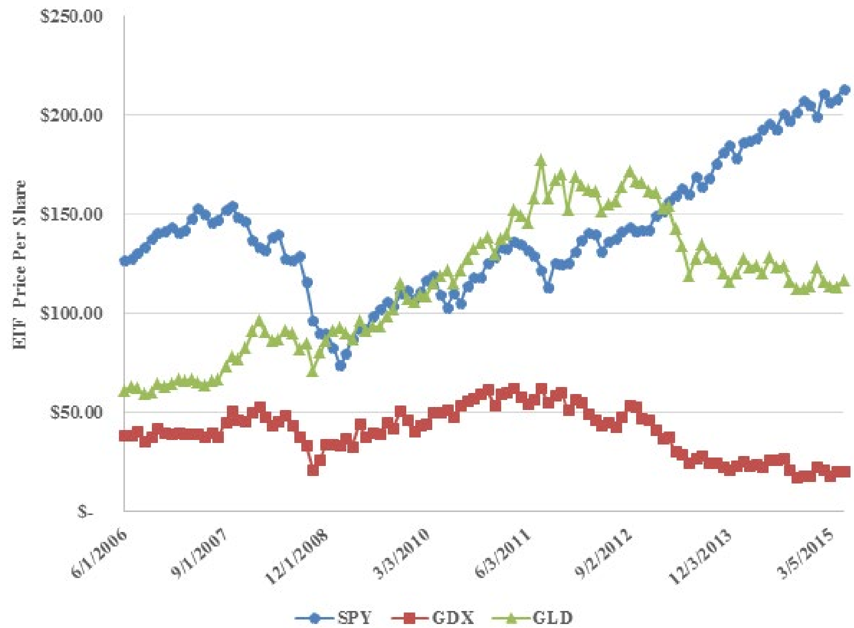

Exhibit 4: Time Series Graph
Source: Author's Calculations
This is a graph showing the price per share of the Market Vectors Gold Miners ETF (GDX), SPDR Gold Shares ETF (GLD), and the SPDR S&P 500 ETF Trust (SPY).

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Endnotes

1. Details are available at www.vaneck.com. For the GLD and SPY ETFs, details are available at www.spdrs.com and www.spdrgoldshares.com. At the suggestion of a reviewer we also examined a global stock portfolio instead of the U.S. only portfolio. When the SPDR Global Dow ETF (DGT) was used instead of SPY, the results were essentially the same. The correlation of returns between SPY and DGT during our sample period was 0.86, 0.94, and 0.94 for daily, weekly, and monthly return data. We report the results using the SPY ETF

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Assessing Risk of Private Equity: What's the Proxy?

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PAAMCO

Overview of Private Equity

As the name suggests, private equity is equity in a company that is privately held and not listed. Therefore public pricing data is not available. Just as the success of hedge funds relies on managers' ability to select individual securities, private equity is a highly heterogeneous asset class in which success is driven by the ability of the managers to pick individual companies. Also similar to hedge funds, private equity funds are structured with a General Partner (GP), who is the private equity fund manager that makes the investment and operating decisions, and Limited Partners (LP), the passive investors in the fund who make no operating or investment decisions. Private equity funds have a fee structure similar to hedge funds as well, with a typical 2% management fee and 20% performance fee (also called the carried interest), usually over a hurdle (or the "preferred return" or "pref"), that is captured at the end of the investment.

Although private equity funds and hedge funds are nominally similar in structure and fees, they are very different in terms of liquidity. Private equity funds have a predetermined life span that lasts about ten years, while hedge funds have an indeterminate life span that allows for monthly or quarterly subscriptions and withdrawals. When an LP makes a commitment to invest in a private equity fund, the commitment generally lasts for the entire life of the fund. There are secondary markets to sell LP stakes in private equity funds, but these markets are small and used infrequently. In addition, while the investment time commitment in a private equity fund is ten years, there are varying periods of cash flows in and out of the fund, and the timing of those cash flows impacts performance (Gottschalg 2013).

When LPs sign documents committing to investment in a private equity fund, they rarely invest capital upfront. The private equity fund assembles all the commitments of capital and then closes for new investments. There can be more than one "close" if there is capacity remaining after the first close. After the fund is closed, the private equity fund will begin to "call" capital for investment. A "capital call" is a notice from the fund, or its GP, to the LPs that it is time to wire money. Once the capital flows in, the GP begins to invest the proceeds; this period of time is called the "investment period." The capital call period and investment period can overlap, and both can last for several years. It is not uncommon to expect capital call periods to last for the first three years of the life of the fund while the investment period can last for five to seven years. In the later life of the fund (i.e., years five to ten), the investments are monetized and cash is distributed back to the LPs (see Exhibit 1). This period is called the "investment realization period." Once all investments have been sold, IPO'd, or written off, the partnership agreement is terminated.

Although there are many flavors of private equity including venture capital, seed investments, angel investing, and acceleration capital, this paper focuses on the largest subcategory—buyouts. Buyouts are relevant for PAAMCO's client base given that our clients and prospects typically make large single allocations, which match the large disbursements of buyout funds. Venture capital funds tend to be smaller, requiring more relationships to meet the capacity needs of large institutions.

Generally, a single private equity fund completes the company acquisition. As can be seen in Exhibit 2 below, the average size of deals is large, over $1 billion.

Private equity sponsors aim to create value in buyout funds in three different ways, or combinations thereof:

1. Improvement of operations: Better management, cost cutting, improved synergies and even additional accretive acquisitions can improve the underlying company's cash flow profile. Leverage in the company decreases as the value of the assets increases as a result of the better cash flow.

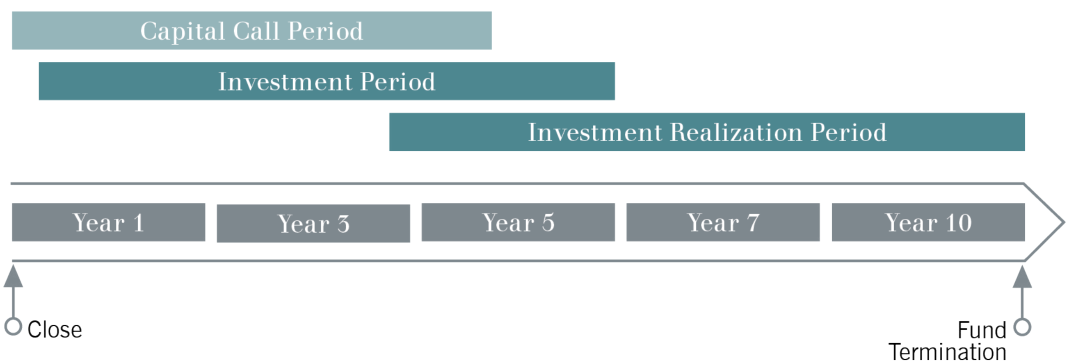
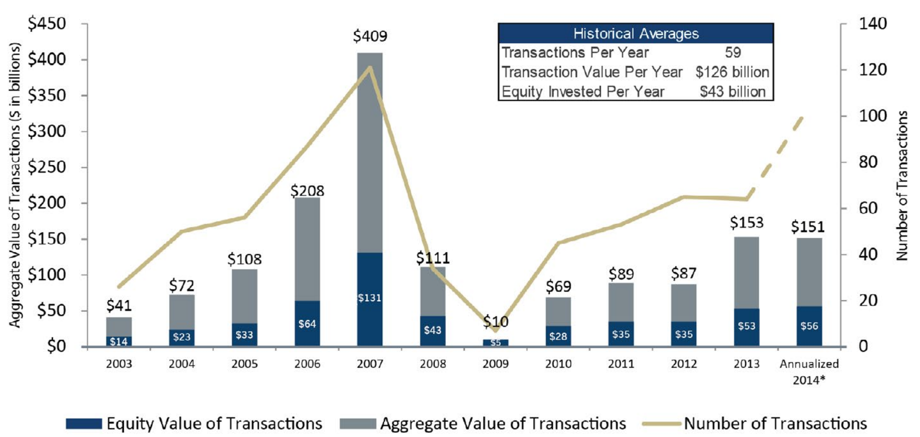


Exhibit 1: Illustration of Private Equity Funding Timeline
Source: PAAMCO



	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014*
Transactions	26	50	56	87	121	34	7	45	53	65	64	104
Average TEV/Deal: (in billions)	$1.6	$1.4	$1.9	$2.4	$3.4	$3.3	$1.4	$1.5	$1.7	$1.3	$2.4**	$1.5

Exhibit 2: Leveraged Buyout (LBO) Activity
Source: S&P Capital IQ Leveraged Buyout Review, as of March 31, 2014
*Q1 2014 Annualized
**Excluding Heinz and Dell: $1.6
Represents U.S LBOs with transaction sizes of $500 million or greater.

2. Financial restructuring: This involves selling off assets (hopefully at attractive valuations) to pay down debt or provide distributions to the LPs. This is generally a riskier strategy as leverage can be substantial, requiring meaningful sales of assets at attractive valuations.

3. Multiple expansion: In times of market dislocation, private equity funds aim to pick up cheap companies trading at low valuations and sell them later as multiples increase. The long time horizon for a fund combined with looser valuation requirements for private equity relieves the GP and the underlying company from much of the mark-to-market volatility of public counterparts.

These characteristics and strategies of buyout funds have implications for assessing their risk profile. First, the underlying companies tend to have a lower beta to the S&P 500, but the use of leverage elevates both the beta and the volatility profile. Second, leverage should generally, but not always, decrease over time. As a result, we would generally expect the volatility profile of a buyout private equity position to be highest in the initial stages, but then decrease over time. However, this expected volatility profile is counter to what is seen in most data series.[1] Third, at a fund level, diversification should provide some benefit as the median buyout fund holds 12 investments (Metrick and Yasuda 2010), so the expected volatility should be somewhere between that of an individual equity and a diversified index. Lastly, the impact of fees on volatility is meaningful and provides a volatility (and beta) dampening impact. Axelson, Sorensen, and Stromberg (2014) find that when constructing private equity IRRs from underlying deal-level data, beta estimates decline from 1.8 gross of fees to 1.3 net of management fees and carried interest. "It appears that subtracting the GP's management fees and carried interest reduces the estimated beta by around 0.5." Venture capital (VC) funds comprise the other largest sector of the private equity industry. VC invests in early-stage companies, typically within the technology or healthcare sectors. At the earliest stages, VC-targeted companies may not even have revenues, so there is rarely any debt or leverage. Funding is provided with a one-to-two year horizon to see if the company can survive, and the failure rate is substantial with about half of VC investments in start-up companies failing (Woodward 2004). VC funds tend to be smaller with an average size of about $300 million (Exhibit 3). As such, private equity portfolios of large institutional investors are more likely to be slanted towards buyout funds. Therefore, VC funds should have a risk assessment that is different and reflects the industry bias and high failure rate, but those issues are left for future research.

Issues with Assessing Risk in Private Equity Investments

Private equity can be thought of as public equity liberated from the obligation to mark-to-market.[2] Although there is a vast literature on private equity funds, there is very little consensus on their risk and return profiles due to a number of factors. Harris (2014) provides an excellent overview of the issues with private equity data. These include: (1) the scarcity of information and quality of data, (2) the time lag of actually receiving funds from an initial investment (fund life is typically ten years with an investment effective duration of five years), (3) smoothed valuation and reporting (quarterly), and (4) the role of fees and treatment of residual interests.

As a result of these issues, beta and alpha estimates for private equity vary quite a bit (see Exhibit 4). Therefore, assessing risk in private equity is a mix of art, based on an understanding of the asset class and the specific investments and strategies pursued by an investor, and science, which gleans some information from the public equity component of private equity (i.e., proxying).

As mentioned, the lack of data accessibility creates a challenge in assessing the risk of private equity investments. First, data on private equity are sparse, highly confidential, and difficult to obtain for research purposes. Second, returns are typically reported only quarterly, which requires a long time series of data

Venture Capital Fund Characteristics (94 funds)				
	25%	median	75%	mean
Size (mm)	$100	$225	$394	$322
# of past funds	0	1	3	1.78
Firm age (years)	0	3	8	4.69
# of partners	3	4	6	4.81
# of professionals	7	9	13	11.49
# of investments	15	20	30	24.24

Buyout Firm Characteristics (144 funds)				
	25%	median	75%	mean
Size (mm)	$297	$600	$1,500	$1,238
First fund dummy				0.27
# of past funds	0	1	3	1.80
Firm age (years)	0	6	11	6.44
# of partners	3	5	7	6.10
# of professionals	9	13	24	20.33
# of investments	9.75	12	16.67	14.76

Exhibit 3: Fund Statistics of Buyout and Venture Capital (VC) Funds
Source: Metrik and Yasuda 2010, The Economics of Private Equity Funds

Buyout Funds

Beta	Annual Alpha	Data Source	Paper	Year	Method
2.20	1.0%	Private large general partner networks	Buchner: The Alpha and Beta of Private Equity Investments	2014	Single factor (S&P 500), cash-flow based, gross of fees
2.20 - 2.40	8.3% - 8.6%	1 Large fund of funds	Axelson, Sorensen, Stromberg: Alpha and Beta of Buyout Deals: A Jump CAPM for Long Term Illiquid Investments	2013	Single factor (S&P 500), cash-flow based, gross of fees
1.33	-2.0%	Preqin	Ang, Chen, Goetzmann, Phalippou: Estimating private equity returns from limited partner cash flows	2013	4 factor Pastor and Stambaugh model, cash-flow based, gross of fees
1.30	0.0%	Center for Private Equity Research (CEPRES)	Franzoni, Nowak, Phalippou: Private equity performance and liquidity risk	2012	4 factor Pastor and Stambaugh model, cash-flow based, gross of fees
0.94	1.6%	Thompson Venture Economics	Driessen, Lin, Phalippou: New Method to estimate risk and return of non-traded assets from cash flows: The case of private equity funds	2011	3 factor Fama French model, cash-flow based
1.00*	-3.0%	Thompson Venture Economics	Phalippou, Gottschalg: The Performance of Private Equity Funds	2009	*Single factor, profitability index (beta is assumed to be 1), net of fees
1.00*	-0.1%	Publicly-listed private equity FoFs, Listed Private Equity Funds	Jegadeesh: Risk and Expected Returns of Private Equity Investments	2009	*Single factor, publicly traded funds (range of betas, but none statistically different from 1), alphas slightly negative
0.41	N/A	Thompson Venture Economics	Kaplan, Schoar: Private Equity Performance: Returns, Persistence, and Capital Flows	2005	Single factor (S&P 500)
0.86	2.0%	Thompson Venture Economics	Woodward: Measuring Risk and Performance for Private Equity	2004	Lagged betas and recalculation
0.66	0.7%	Thompson Venture Economics	Jones, Rhodes-Kropf: The Price of Diversifiable Risk in Venture Capital and Private Equity	2003	Single factor (S&P 500), GP estimates of NAV
1.08	N/A	1 Large LP	Ljungqvist, Richardson: The Cash Flow, Return, and Risk Characteristics of Private Equity	2003	Single factor (S&P 500)

Venture Capital Funds

Beta	Annual Alpha	Data Source	Paper	Year	Method
2.60	3.5%	Private large general partner networks	Buchner: The Alpha and Beta of Private Equity Investments	2014	Single factor (S&P 500), cash-flow based
2.57	-8.3%	Thompson Venture Economics	Driessen, Lin, Phalippou: New Method to estimate risk and return of non-traded assets from cash flows: The case of private equity funds	2008	3 factor Fama French model, cash-flow based
2.06	-1.2%	Cambridge Associates	Woodward: Measuring Risk and Performance for Private Equity	2004	Lagged betas and recalculation

Exhibit 4: Summary of Beta Findings in Academic Literature
Source: Referenced papers, PAAMCO

(i.e., five to six years) in order to evaluate the asset class. Third, as with hedge fund indices, there are various biases in index data such as selection bias, hindsight bias, and backfill bias. Some indices gather information from GPs, others from LPs and GPs, and still others use the Freedom of Information Act (FOIA) to obtain information from the GPs and investors. Lastly, there is significant debate about the use of residuals in indices. Since private equity investments are illiquid, a fund's remaining investment in a company may exist for a period of years with no change in the valuation (similar to a hedge fund residual). If indices include residual investments, this has the impact of adding 0% returns quarter after quarter which can both bias the return estimates (typically down) and dampen the volatility of the overall return stream. The Burgiss[3] data is generally considered to be the best since it is based on actual accounting cash flows from the LPs and the data can be crosschecked and verified across multiple LPs and GPs. Cambridge Associates has the largest database of reporting funds and is perhaps the most widely used given the availability of data to the public. Similar to Burgiss, Cambridge Associates' private equity indices are constructed from the underlying cash flows and Net Asset Value (NAV) provided by the GPs. While performance results show that Cambridge Associates and Preqin are qualitatively similar to the Burgiss data, Preqin data is primarily constructed through Freedom of Information Act (FOIA) requests, making it difficult to verify the reported numbers. Venture Economics is currently considered the least robust database due to its inclusion of funds that stopped reporting and its practice of rolling forward the last reported NAVs every quarter (Harris 2014). While Burgiss data may be the best data source, it is also not public, so Cambridge Associates indices are used for analytical purposes in this paper.

The time horizon of private equity investing also creates challenges with interpreting return data. The legal structure of a private equity fund's life is typically eight to ten years, and the true success of an investment isn't known until the fund is wound down. Nonetheless, investors still expect a status update on their investment, thus creating the need for quarterly performance results. Historically, private equity funds could hold investments at cost which resulted in a very smooth return series that far understated the risk. For example, assume a private equity fund has an NAV of $100 based on the cost of acquiring properties. The market for the following two months is +10% and -5%. The PE fund NAV will not reflect that volatility, but rather remain static at $100. With cost basis accounting, the volatility could be flat until there is a market realizing event.

The implementation of accounting rule SFAS 157 (also referred to as ASC 820) in 2007 requires fair value reporting of the investments, which should increase return volatility. Even so, valuations are largely model-based (i.e., a discounted cash flow analysis) and so will likely still exhibit a smooth pattern. For example, a discounted cash flow analysis is one acceptable method of determining fair value for an illiquid investment. In these examples, the quarterly NAV will change mostly due to a set of cash flow payments rolling off. Since the model remains static except with timing moving forward one period, a high degree of autocorrelation that continues to understate volatility is created. Other model-based methods such as comparable sales would also continue to understate volatility due to the infrequency of relevant deals. While fair value reporting moves the valuation of private equity investments closer to the "true" value, the scarcity of relevant information to evaluate private equity positions and the numerous methods to determine fair value continue to result in an understated volatility profile for private equity.

In addition, LPs minimally scrutinize whether GPs determine "true" NAV value because LPs do not typically transact at that value. This is in contrast to hedge fund managers for whom an accurate estimate of the monthly NAV is important because investors may invest or redeem at that value. As a result, hedge funds are subject to heavy scrutiny and even outside pricing verification to establish an accurate NAV. Private equity fund investors are locked for the duration of the life of the fund, so the quarterly NAV value does little else than serve as a reporting value. The degree of scrutiny is much lower and there is rarely an outside or objective pricing review of the securities (and even if there were, the GP would have a substantial information advantage).

Investors view private equity returns in two different ways. One way is to evaluate returns by fund vintage year, a method mostly used for benchmarking purposes to determine if a fund is outperforming its peers. The other way is by quarterly index releases for the asset class that combine vintage years to report a quarterly return series. This index data is built upon a vast array of assumptions, mostly because recent vintages will report quarterly return series with only a fraction of the investments realized. For example, in Exhibit 5 below from Harris (2014), we see that in the final eight years of analysis, just over a quarter of the funds have investments that have been realized with capital returned to investors. This means that the return profile is biased heavily by the GP valuation assumptions for company performance rather than actual cash proceeds realized.

The fee structure of private equity investments is somewhat unique and adds to the challenges of assessing risk. Fees are paid on the committed capital as opposed to the invested capital, which is the practice for hedge funds. In addition, the fees are high: 2% management fee and 20% performance fee earned at the realization of the investment, and various transaction and monitoring fees. Index data, like Cambridge Associates, typically report net of fee data, but the fees can have a volatility dampening effect thereby skewing beta and volatility estimates downward.

Buyout Funds								
			Internal Rate of Return			Investment Multiple		
Vintage Year	Funds	Median % Realized	Average	Median	Weighted Average	Average	Median	Weighted Average
1984	2	100.0	10.6	10.6	15.8	2.44	2.44	3.28
1985	1	100.0	13.7	13.7	13.7	2.66	2.66	2.66
1986	5	100.0	13.6	16.8	16.0	2.40	2.36	3.27
1987	7	100.0	17.3	16.2	15.3	2.93	2.55	2.58
1988	7	100.0	14.4	10.1	18.4	2.03	1.74	2.32
1989	8	100.0	20.6	22.4	21.1	2.55	2.69	2.75
1990	2	97.8	31.9	31.9	52.9	3.03	3.03	3.37
1991	4	100.0	24.7	24.9	27.8	2.45	2.54	2.54
1992	5	100.0	11.2	10.7	15.0	1.68	1.41	1.88
1993	11	100.0	31.0	19.1	26.0	2.62	2.07	2.48
1994	13	100.0	29.6	24.7	34.5	2.73	2.18	3.29
1995	17	99.5	20.9	10.5	16.9	2.08	1.51	1.82
1996	9	100.0	6.0	5.7	2.4	1.46	1.30	1.17
1997	30	98.3	8.6	5.5	8.8	1.42	1.28	1.50
1998	38	96.9	6.4	8.0	3.6	1.42	1.39	1.28
1999	28	89.9	3.3	4.3	4.8	1.31	1.21	1.40
2000	39	62.2	12.7	11.9	14.3	2.66	1.58	1.75
2001	26	57.5	13.7	14.6	15.1	1.57	1.72	1.67
2002	21	44.9	16.1	16.4	18.4	1.72	1.79	1.84
2003	13	29.4	19.5	16.2	22.5	1.98	1.75	1.80
2004	46	18.1	12.8	11.7	15.4	1.53	1.50	1.64
2005	57	9.7	6.8	7.6	7.1	1.26	1.25	1.27
2006	67	10.8	2.6	1.2	0.5	1.08	1.03	1.02
2007	74	1.9	3.7	6.2	4.4	1.11	1.12	1.09
2008	68	6.3	3.2	2.8	1.5	1.07	1.04	1.04
Average	598	72.9	14.2	13.0	15.7	1.97	1.81	2.03
Average 1980s	30	100.0	15.0	14.9	16.7	2.50	2.41	2.81
Average 1990s	157	98.2	17.5	14.6	19.3	2.02	1.79	2.07
Average 2000s	411	26.8	10.1	9.8	11.0	1.55	1.42	1.46

Exhibit 5: Historical IRRs and Investment Multiples for Private Equity Returns
Source: Harris et al., (2014)

Although the management fee has zero beta for private equity since it is based on the committed capital and therefore remains constant, the performance fee has a meaningful impact on beta estimates which we can estimate as 20% carried interest multiplied by the gross of fees beta. This volatility and beta dampening effect occurs because the performance fee accrual reduces returns as the expected deal value increases (typically in rising equity markets), while the reversal of the performance fee accrual increases returns as the expected deal value decreases (typically in falling equity markets).

Approaches to Assess Private Equity Risk

The expanding body of academic literature recognizes that private equity has a beta and volatility profile higher than that suggested by the smooth quarterly returns of major index providers. Multiple approaches can be used to assess risk more appropriately for private equity, including: 1) using statistical processes to de-smooth the reported return streams; 2) using proxies from publicly-listed private equity companies; or 3) using publicly-listed industry or size (or both) index proxies. This section examines each of these approaches in turn.

(1) De-smoothing returns

A large portion of academic literature attempts to calculate the beta, volatility, and alpha estimates of private equity funds by using the reported return streams and applying statistical techniques to de-smooth the returns. One of these methods is illustrated in Jorion (2012) which uses the autocorrelation coefficient to construct an adjusted return series. To illustrate, we examine the Cambridge Associates private equity returns from March 2005 to September 2014. For this illustration, we used a one period autocorrelation coefficient, although arguably the autocorrelation impact could extend for up to four or five periods.

Exhibit 6 compares the properties of the S&P 500 Total Return Index, the raw Cambridge Associates return series, and the de-smoothed Cambridge Associates series. We can see that the volatility increases meaningfully from 9.6% to 16.6% for the de-smoothed series. This is a 72% increase in the volatility measure alone. Similarly, the Sharpe ratio, which provides a measure of risk-adjusted return, plummets below 1 due to the increase in volatility. Lastly, the S&P 500 beta of private equity also meaningfully increases as the diversifying properties of private equity were overstated due to the lagged and smoothed return series. These findings are in line with what has been published.

As we can see in Exhibit 7 below, the de-smoothing series generally tracks the return pattern of the original but with greater volatility, which seems more realistic. As a result, for the purpose of this paper, the de-smoothed return series will be treated as the "true" return series, against which we compare proxies using public market-based substitutes.

	S&P 500	CA Private Equity	Adjusted CA PE Returns
Return	8.51%	13.65%	13.78%
Volatility	16.45%	9.64%	16.63%
Sharpe ratio	0.517	1.416	0.829
Autocorrelation coefficient	0.247	0.487	0.020
Beta to S&P	1.00	0.46	0.74

Exhibit 6: Impact of De-smoothing Private Returns
Source: Cambridge Assicates, PAAMCO

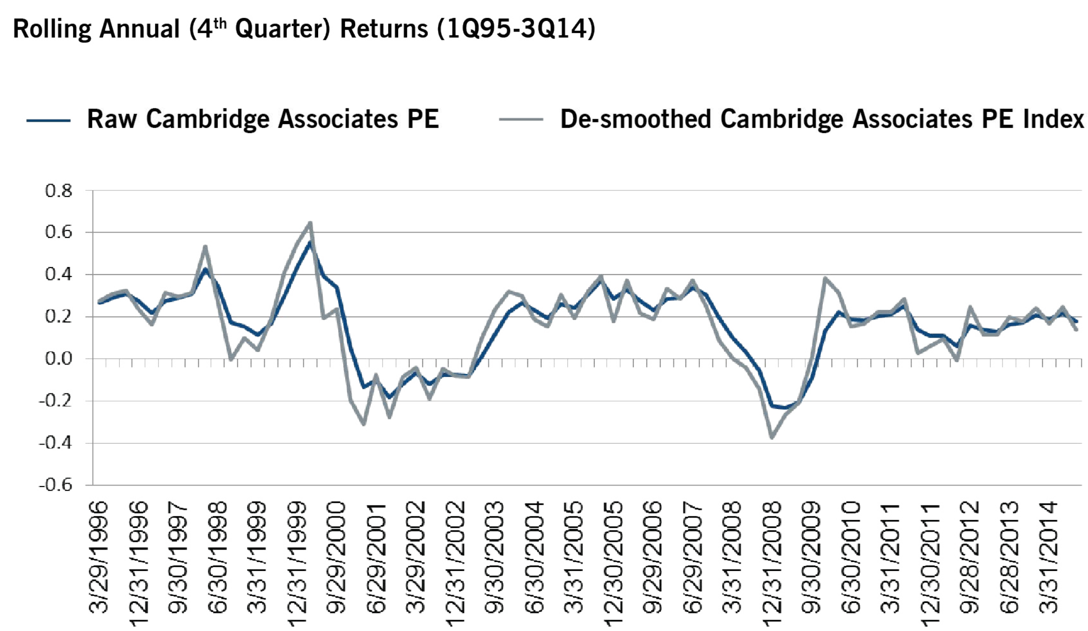


Exhibit 7: Comparison of Smoothed vs. De-smoothed Private Equity Returns
Source: Cambridge Assicates, PAAMCO

(2) Publicly-listed private equity companies

As noted previously, PE indices have a number of different biases that can skew the return estimates, most notably incomplete information and a selection bias. For example, with the exception of Burgiss, most PE indices are not based on fund-level cash flow data. Since the timing of capital calls and distributions can impact IRRs, the cash flow-based data is important for deriving accurate returns. Also, selection bias is large as many indices are based on voluntary reporting either by the GPs or the LPs. These data sets can be skewed upwards by those LPs having a good experience from their private equity investments or by GPs ramping up marketing efforts on the heels of a successful fund. Lastly, some data sets such as Preqin lean more heavily on FOIA requests. These databases could exclude large successful funds that avoid taking institutional assets specifically to avoid FOIA requests.

Evaluating the performance of publicly-listed private equity funds or funds of hedge funds seeks to eliminate these biases, and the academic research finds that using listed private equity funds provides similar beta and alpha expectations as de-smoothing methods (Jegadeesh, Kraussl, and Pollet 2009). Listed private equity as a proxy provides a similar framework to using funds of hedge funds returns to evaluate hedge fund returns.

The use of publicly-listed private equity funds takes a large step towards using public market pricing to establish the "true" return streams for private equity, but it is also a flawed measure. Most notably, the market prices of listed private equity companies are more likely to represent a claim on private equity fees, not the companies themselves. While growth in fees (particularly the more stable management fee) is related to growth in assets which in turn can be a proxy for growth of the underlying companies, it does not provide a direct link to understanding the volatility profile of a private equity fund of companies. The claim on fees can also induce a leverage effect, as incentive fees typically account for 20% of gross returns instead of the 80% going to LP investors.

Top 10 Constituents by Index Weight

Constituent	Symbol	Sector*
Brookfield Asset Management Inc	BAM.A	Financials
Partners Group Hldg	PGHN	Financials
Blackstone Group LP The	BX	Financials
3I Group	III	Financials
KKR & Co	KKR	Financials
Eurazeo	RF	Financials
Ares Capital Corp	ARCC	Financials
Wendel	MF	Financials
American Capital Ld	ACAS	Financials
Intermediate Capital Group	ICP	Financials

Exhibit 8: Listed Private Equity Funds in S&P Listed Private Equity Index
Source: Standard & Poors
*Based on GICS sectors

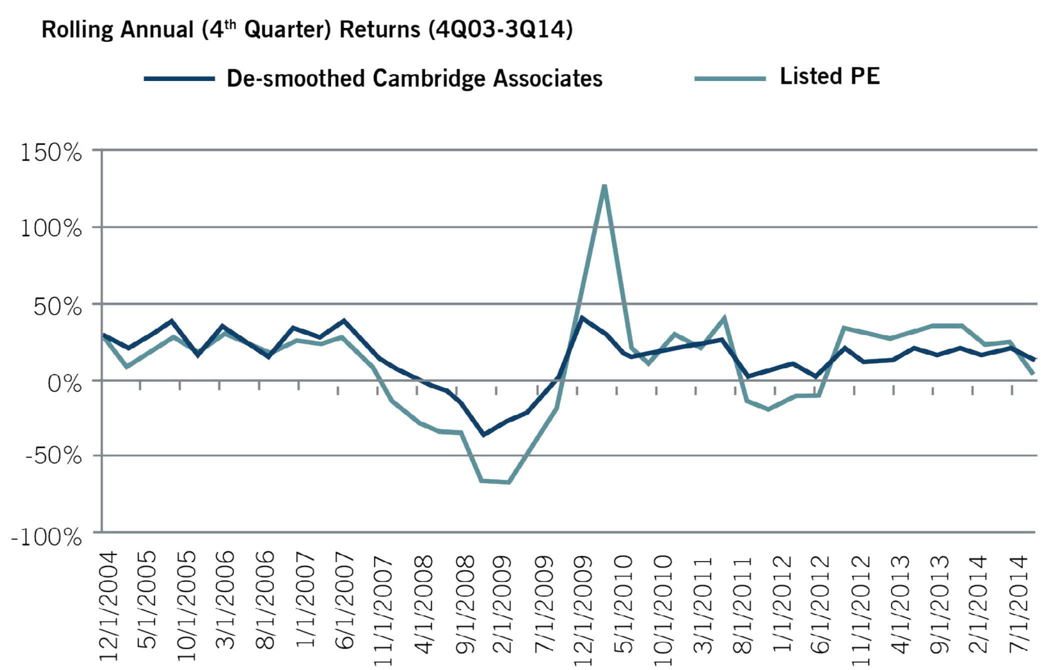


Exhibit 9: Listed Private Equity Returns
Source: S&P Cambridge Associates, PAAMCO

In addition, the largest listed private equity companies do substantially more than just private equity. If we evaluate the S&P Listed Private Equity Index as a proxy (see Exhibit 8 on the previous page), the largest weights (e.g., Blackstone, Brookfield, KKR) have other business lines in addition to private equity, such as hedge funds and real estate. Lastly, as seen in Exhibit 9 on the previous page, the volatility profile of listed private equity companies seems to be too large, as compared to the de-smoothed Cambridge Associate returns. This methodology is also not ideal for assessing the risk in private equity because the risk and return profile of these companies is driven by factors other than the risk in a private equity investment itself and because the volatility of this proxy appears to overstate the true risk of the asset class.

(3) Industry and size ETF proxies

Mapping private equity allocations to industry and size sector ETFs provides a basic intuition for how private equities perform. After all, for buyout funds, these are companies that typically were publicly listed before the private equity company took them private and that will be publicly listed (or acquired by a publicly listed company) as the private equity fund winds down. Per the Bain 2015 Global Private Equity Report, when referring to the number of private equity IPOs, "the new IPOs also understate in other ways the importance of public equity markets as an exit venue for private equity." Using industry proxies is also the basis for the MSCI Barra factor model for private equity.

If we proceed with industry and size index proxies, the question of which proxies are appropriate remains. The bulk of global buyout deal value is in the $1-$5 billion range, which corresponds to midcap companies (see Exhibit 10).

Similarly to hedge fund investors, private equity investors look for dislocations such as the financial crisis that began in 2008 or the energy sell-off beginning in 2H 2014 as opportunities to deploy capital. However, we know some general characteristics of industry exposures given the types of companies buyout funds seek—generally those with strong cash flows, low beta, and an ability to improve operations or revenues through financial restructuring. Exhibit 11 illustrates that in any given year the industry exposures fluctuate. We see that the largest concentrations are relatively stable in industries such as technology, industrials, services, and transportation.

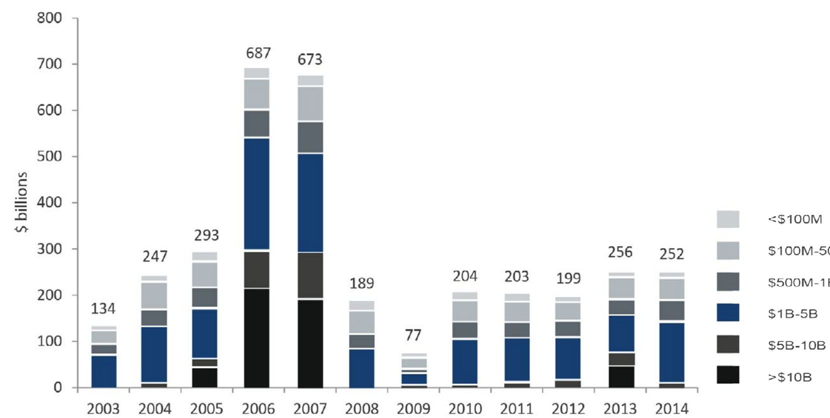


Exhibit 10: Global Buyout Deal Value by Size
Source: Dealogic, PAAMCO

Year	Finance	Food	Health	High-tech	Industrial	Natural Resources	Retail	Services	Transport
1990	1%	16%	9%	10%	21%	0%	6%	31%	7%
1991	6%	12%	2%	15%	14%	4%	5%	36%	6%
1992	5%	11%	1%	9%	39%	14%	1%	15%	5%
1993	24%	25%	6%	6%	21%	1%	3%	8%	6%
1994	4%	5%	2%	28%	19%	8%	13%	9%	12%
1995	7%	4%	9%	5%	24%	4%	12%	21%	14%
1996	15%	1%	7%	9%	27%	4%	4%	19%	14%
1997	9%	7%	20%	13%	17%	3%	10%	17%	5%
1998	7%	9%	4%	8%	26%	4%	7%	29%	5%
1999	7%	4%	7%	17%	27%	3%	2%	26%	6%
2000	3%	15%	6%	20%	28%	5%	3%	9%	13%
2001	3%	4%	15%	12%	28%	6%	3%	22%	6%
2002	7%	13%	11%	2%	22%	3%	3%	16%	23%
2003	4%	7%	3%	29%	19%	3%	8%	15%	12%
2004	4%	1%	10%	8%	33%	3%	13%	12%	15%
2005	12%	3%	10%	16%	32%	5%	3%	14%	6%
2006	1%	5%	7%	25%	17%	6%	6%	24%	9%
2007	3%	0%	5%	6%	28%	5%	12%	32%	9%
2008	1%	5%	7%	25%	17%	6%	6%	24%	9%
2009	1%	5%	7%	25%	17%	6%	6%	24%	9%
Average	6%	8%	7%	14%	24%	5%	6%	20%	10%

Exhibit 11: Global Buyout Deal Value by Industry
Source: HEC Buyout Dataset, Gottschalg et al., 2013

If we take the average weight allocated to these sub-industries from 1990-2009 and use the S&P 400 Midcap Index sectors to create a proxy, we obtain a risk and return profile that can be compared to both the raw and de-smoothed Cambridge Associates times series (see Exhibit 12).

As shown in Exhibit 13, this industry/index proxy has a risk profile that most closely approximates the de-smoothed private equity index. The volatility is similar, albeit slightly higher. The beta is higher, in large part due to higher correlation with the market.

Thus, using an industry-based and size-based index proxy appears to be a good fit for approximating the risk profile of private equity positions. This implementation, however, can still be improved upon. Like hedge funds, private equity funds are actively managed and opportunistic. This can result in industry weights for a particular vintage that look very different from the average weight used in our proxy. In practice, the industry weights can be adjusted to reflect the opportunity set or the known details of a particular investor's portfolio.

Indeed, PAAMCO goes through a systematic process of mapping the private equity positions in our clients' portfolios using publicly traded proxies. Our risk management team consults with our portfolio management team to determine the best proxy, usually a single stock in the same industry with the same size, or an industry index. Sometimes an adjustment is made for leverage. An industry index obviously understates the risk at the level of the individual position, but we believe this effect washes out at the portfolio level.

Conclusion

Private equity is a growing asset class for institutional investors, yet its risk characteristics are largely elusive. These difficulties emanate from the lack of liquidity in private equity markets, smooth NAV valuation processes, and sparse, flawed data sets. In addition, the success of a private equity investment is not truly known until the investment is realized and exited, typically ten years after the initial capital commitment. The timing of cash flows and the equity market conditions upon exit of investment (i.e., the multiple for the underlying companies) are meaningful drivers of the IRR.

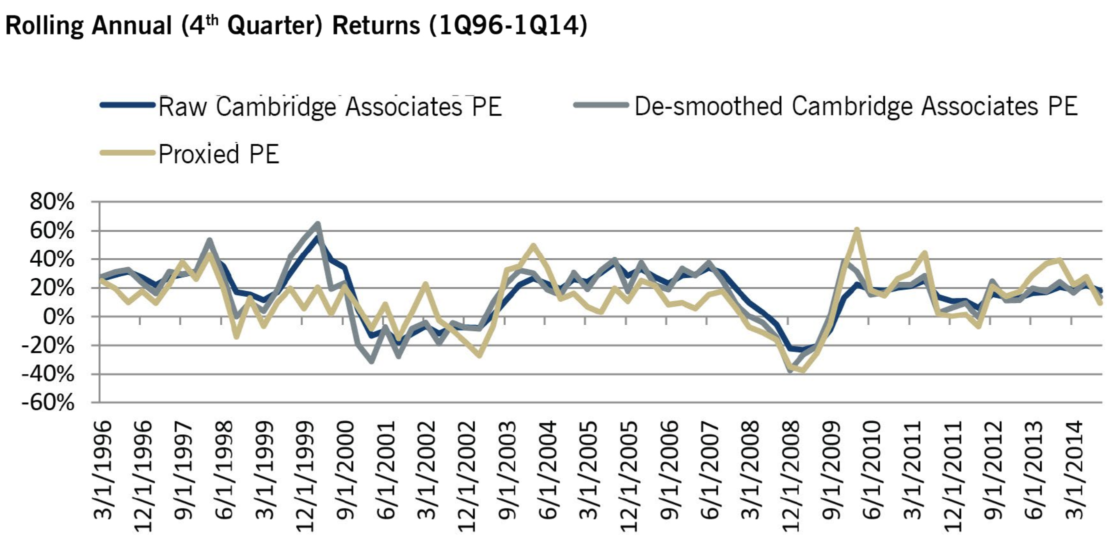


Exhibit 12: Comparison of Public Proxied Private Equity Returns
Source: Cambridge Associates, PAAMCO

Since 1Q 2004

	Raw Cambridge Associates PE	De-smoothed Cambridge Associates PE	Proxied PE	S&P 500	Listed PE
Return	14.6%	13.9%	11.1%	8.7%	11.2%
Volatility	9.9%	18.4%	19.9%	15.8%	32.3%
Sharpe Ratio	1.5	0.8	0.6	0.6	0.3
Autocorrelation Coefficient	38.5%	-16.8%	12.3%	21.9%	19.7%
Beta to S&P 500	0.5	0.8	1.2	1.0	1.8
N=	43	43	43	43	43
Lehman (3Q08-1Q09)	-24.0%	-29.5%	-39.1%	-36.4%	-64.1%
Fall '11 (3Q11-4Q11)	1.1%	1.8%	-6.5%	-2.1%	-18.7%

Exhibit 13: Summary Statistics of PE Proxy Alternatives
Source: Cambridge Associates, Bloomberg, PAAMCO

Most academic research centered on determining the beta and alpha of PE funds tended to use lagged betas or statistical techniques to de-smooth reported return series. While this is helpful ex-post to assess the pattern of the risk profile, it is not helpful in conducting the forward-looking analysis needed to make asset allocation decisions, nor is it helpful in understanding the risk drivers of the allocation. Other academic research uses public market proxies, such as listed private equity funds. However, listed private equity funds exhibit much higher volatility as their returns represent a different and leveraged claim on the underlying assets. Overall, proxies based on industry and size appear to provide the closest match to de-smoothed private equity index returns and hence offer a practical and useful approximation to risk measurement for private equity.

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Endnotes

1. Since private equity positions are not actively traded, the valuation is typically model-based (such as a discounted cash flow model) and the value is only reported quarterly. However, once a company is listed through an Initial Public Offering (IPO), the price will change daily as the shares are more actively traded. Looking at the standard deviation of the reported values, we typically see lower volatility in the earlier years followed by higher volatility as more information becomes public and the shares start to trade on a daily basis.
2. Valuation has become more disciplined for private equity investments because of changes in the accounting rules imposed by SFAS 157 (or ASC 820) and subsequently, the SEC launch of a late 2011 informal inquiry into the private equity industry. While prior to the release of ASC 820, private equity firms were allowed to value investments based on cost, they now need to use fair value. The most important assumption for private equity valuation is the assumed exit price and the soundness of the assumptions used to estimate that exit price.
3. Burgiss is a global provider of investment decision support tools for the private capital market. They offer tools for a variety of portfolio monitoring and performance measurement functions.

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Understanding the Kelly Capital Growth Investment Strategy

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Introduction to the Kelly Capital Growth Criterion and Samuelson's Objections to it

The Kelly capital growth criterion, which maximizes the expected log of final wealth, provides the strategy that maximizes long run wealth growth asymptotically for repeated investments over time. However, one drawback is found in its very risky behavior due to the log's essentially zero risk aversion; consequently it tends to suggest large concentrated investments or bets that can lead to high volatility in the short-term. Many investors, hedge funds, and sports bettors use the criterion and its seminal application is to a long sequence of favorable investment situations.

Edward Thorp was the first person to employ the Kelly Criterion, or "*Fortune's Formula*" as he called it, to the game of blackjack. He outlines the process in his 1960 book *Beat the Dealer* and his findings changed the way this game was played once he had demonstrated that there was a winning strategy. As applied to finance, a number of note-worthy investors use Kelly strategies in various forms, including Jim Simons of the Renaissance Medallion hedge fund.

The purpose of this paper is to explain the Kelly criterion approach to investing through theory and actual investment practice. The approach is normative and relies on the optimality properties of Kelly investing. There are, of course, other approaches to stock and dynamic investing. Besides mean-variance and its extensions there are several important dynamic theories. Many of these are surveyed in MacLean and Ziemba (2013). An interesting continuous time theory based on descriptive rather than normative concepts with arbitrage and other applications is the stochastic portfolio theory of Fernholz and colleagues, see for example, Fernholz and Shay(1982), Fernholz (2002), and Karatzas and Fernholz (2008). They consider the long run performance of portfolios using specific distributions of returns such as lognormal. The Kelly approach uses a specific utility function, namely log, with general asset distributions.

What is the Kelly Strategy and what are its main properties?

Until Daniel Bernoulli's 1738 paper, the linear utility of wealth was used, so the value in ducats would equal the number of ducats one had. Bernoulli postulated that the additional value was less and less as wealth increased and was, in fact, proportional to the reciprocal of wealth so,

$$u'(w) = 1/w \text{ or } u(w) = \log(w)$$

where u is the utility function of wealth w, and primes denote differentiation. Thus concave log utility was invented.

In the theory of optimal investment over time, it is not quadratic (one of the utility function behind the Sharpe ratio), but log that yields the most long-term growth asymptotically. Following with an assessment of that aspect, the Arrow-Pratt risk aversion index for log(w) is:

$$R_A(w) = -\frac{u''}{u'} = \frac{1}{w}$$

which is essentially zero. Hence, in the short run, log can be an exceedingly risky utility function with wide swings in wealth values.

John Kelly (1956) working at Bell Labs with information theorist Claude Shannon showed that for Bernoulli trials, that is win or lose 1 with probabilities p and q for $p+q=1$, the long run growth rate, G, namely

$$G = \lim_{t\to\infty} \log \left\{ \frac{w_t}{w_0} \right\}^{1/t}$$

where t is discrete time and w_1 is the wealth at time t with w_0 the initial wealth is equivalent to $\max E\,[\log w]$

Since $w_t = (1+f)^M\,(1-f)^{t-M}$ is the wealth after t discrete periods, f is the fraction of wealth bet in each period and M of the t trials are winners.

Then, substituting W_t into G gives

$$G = \lim_{t\to\infty} \left\{ \frac{M}{t}\log(1+f) + \frac{t-M}{t}\log(1-f) \right\} + p\log(1+f) + q\log(1-f)$$

and by the strong law of large numbers

$$G = E\left[\log w\right]$$

Thus the criterion of maximizing the long run exponential rate of asset growth is equivalent to maximizing the one period expected logarithm of wealth. So an optimal policy is myopic in the sense that the optimal investments do not depend on the past or the future. Since

$$\max G(f) = p\log(1+f) + q\log(1-f)$$

the optimal fraction to bet is the edge $f^* = p - q$. The edge is the expected value for a bet of one less the one bet. These bets can be large. For example, if p=0.99 and q=.01, then f^*= 0.98, that is 98% of one's fortune. Some real examples of very large and very small bets appear later in the paper. If the payoff odds are +B for a win and -1 for a loss, then the edge is $Bp - q$ and

$$f^* = \frac{Bp - q}{B} = \frac{edge}{odds}$$

So the size of the investments depend more on the odds, that is to say, the probability of losing, rather than the mean advantage. Kelly bets are usually large and the more attractive the wager, the larger the bet. For example, in the trading on the January turn-of-the-year effect with a huge advantage, full Kelly bets approach 75% of initial wealth. Hence, Clark and Ziemba (1988) suggested a 25% fractional Kelly strategy for their trades, as discussed later in this article.

Latane (1959, 1978) introduced log utility as an investment criterion to the finance world independent of Kelly's work. Focusing, like Kelly, on simple intuitive versions of the expected log criteria, he suggested that it had superior long run properties. Chopra and Ziemba (1993) have shown that in standard mean-variance investment models, accurate mean estimates are about twenty times more important than covariance estimates and ten times variances estimates in certainty equivalent value. But this is risk aversion dependent with the importance of the errors becoming larger for low risk aversion utility functions. Hence, for $\log w$ with minimal risk aversion, the impact of these errors is of the order 100:3:1. So bettors who use $E\log$ to make decisions can easily over bet.

Leo Breiman (1961), following his earlier intuitive paper Breiman (1960), established the basic mathematical properties of the expected log criterion in a rigorous fashion. He proved three basic asymptotic results in a general discrete time setting with intertemporally independent assets.

Suppose in each period, N, there are K investment opportunities with returns per unit investe $X_{N_1}, \ldots, X_{N_K}$. Let $\Lambda = (\Lambda_1, \ldots, \Lambda_K)$ be the fraction of wealth invested in each asset. The wealth at the end of period N is

$$w_N = \left(\sum_{i=1}^{K} \Lambda_i X_{Ni} \right) w_{N-1}.$$

In each time period, two portfolio managers have the same family of investment opportunities, X, and one uses a Λ which maximizes $E\log w_N$ whereas the other uses an *essentially different* strategy, Λ, so they differ infinitely often, that is,

$$E\log w_N \Lambda^* - E\log w_N(\Lambda) \to \infty.$$

Then

$$\lim_{N\to\infty} \frac{w_N\left(\Lambda^*\right)}{w_N\left(\Lambda\right)} \to \infty$$

So the wealth exceeds that with any other strategy by more and more as the horizon becomes more distant. This generalizes the Kelly Bernoulli trial setting to intertemporally independent and stationary returns.

The expected time to reach a preassigned goal A is asymptotically least as A increases with a strategy maximizing $E\log w_N$. Assuming a fixed opportunity set, there is a fixed fraction strategy that maximizes $E\log w_N$, which is independent of N.

Probability of Winning	Odds	Probability of Being Chosen in the Simulation at at Each Decision Point	Optimal Kelly Bets Fraction of Current Wealth
0.57	1-1	0.1	0.14
0.38	2-1	0.3	0.07
0.285	3-1	0.3	0.047
0.228	4-1	0.2	0.035
0.19	5-1	0.1	0.028

Exhibit 1: The Investments
Source: Ziemba and Hausch (1986)

Final Wealth Strategy	Min	Max	Mean	Median	Number of times the final wealth out of 1000 trials was >500	>1000	>10,000	>50,000	>100,000
Kelly	18	483,883	48,135	17,269	916	870	598	302	166
Half Kelly	145	111,770	13,069	8,043	990	954	480	30	1

Exhibit 2: Statistics of the Simulation
Source: Ziemba and Hausch (1986)

Consider the example described in Exhibit 1. There are five possible investments and if we bet on any of them, we always have a 14% advantage. The difference between them is that some have a higher chance of winning than others. For the latter, we receive higher odds if we win than for the former. But we always receive 1.14 for each 1 bet on average. Hence we have a favorable game. The optimal expected log utility bet with one asset (here we either win or lose the bet) equals the edge divided by the odds. So for the 1-1 odds bet, the wager is 14% of ones fortune and at 5-1 its only 2.8%. We bet more when the chance that we will lose our bet is smaller. Also, we bet more when the edge is higher. The bet is linear in the edge so doubling the edge doubles the optimal bet. However, the bet is non-linear in the chance of losing our money, which is reinvested so the size of the wager depends more on the chance of losing and less on the edge.

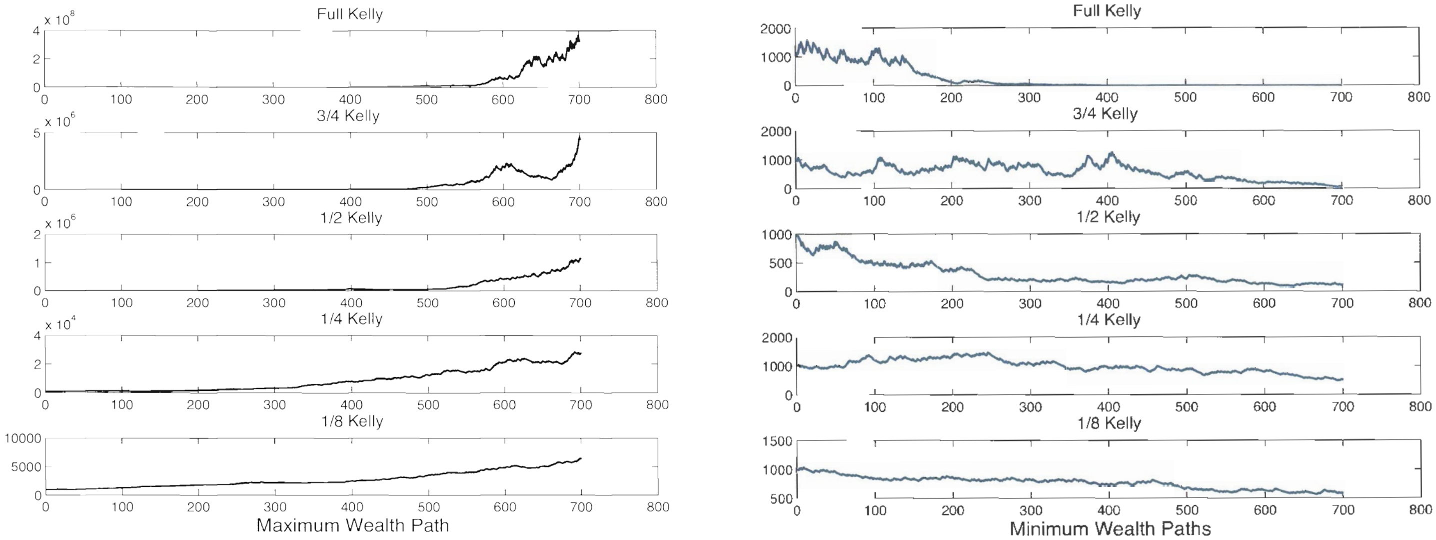
The simulation results shown in Exhibit 2 assume that the investor's initial wealth is $1,000 and that there are 700 investment decision points. The simulation was repeated 1,000 times. The numbers in Exhibit 2 are the number of times out of the possible 1,000 that each particular goal was reached. The first line is with log or Kelly betting. The second line is half Kelly betting. That is, you compute the optimal Kelly wager but then blend it 50-50 with cash. For lognormal investments α-fractional Kelly wagers are equivalent to the optimal bet obtained from using the concave risk averse, negative power utility function, $-w^{-\beta}$, where $\alpha = \frac{1}{1-\beta}$. For non lognormal assets this is an approximation (see MacLean, Ziemba and Li, 2005 and Thorp, 2010, 2011). For half Kelly (α=1/2), β=-1 and the utility function is $-w^{-1} = -1/w$. Here the marginal increase in wealth drops off as w^2, which is more conservative than log's w. Log utility is the case $\beta \to -\infty$, α=1 and cash is $\beta \to -\infty$, α=0.

A major advantage of full Kelly log utility betting is the 166 in the last column. In fully 16.6% of the 1,000 cases in the simulation, the final wealth is more than 100 times as much as the initial wealth. Also in 302 cases, the final wealth is more than 50 times the initial wealth. This huge growth in final wealth for log is not shared by the half Kelly strategies, which have only 1 and 30, respectively, for these 50 and 100 times growth levels. Indeed, log provides an enormous growth rate but at a price, namely a very high volatility of wealth levels. That is, the final wealth is very likely to be higher than with other strategies, but the wealth path will likely be very bumpy. The maximum, mean, and median statistics in Exhibit 2 illustrate the enormous gains that log utility strategies usually provide.

Let us now focus on bad outcomes. The first column provides the following remarkable fact: one can make 700 independent bets of which the chance of winning each one is at least 19% and usually is much more, having a 14% advantage on each bet and still turn $1,000 into $18, a loss of more than 98%. Even with half Kelly, the minimum return over the 1,000 simulations was $145, a loss of 85.5%. Half Kelly has a 99% chance of not losing more than half the wealth versus only 91.6% for Kelly. The chance of not being ahead is almost three times as large for full versus half Kelly. Hence to protect ourselves from bad scenario outcomes, we need to lower our bets and diversify across many independent investments.

Exhibit 3 shows the highest and lowest final wealth trajectories for full, $\frac{3}{4}$, $\frac{1}{2}$, $\frac{1}{4}$ and $\frac{1}{8}$ Kelly strategies for this example. Most of the gain is in the final 100 of the 700 decision points. Even with these maximum graphs, there is much volatility in the final wealth with the amount of volatility generally higher with higher Kelly fractions. Indeed with $\frac{3}{4}$ Kelly, there were losses from about decision points 610 to 670.

The final wealth levels are much higher on average, the higher the Kelly fraction. As you approach full Kelly, the typical final wealth escalates dramatically. This is shown also in the maximum wealth levels in Exhibit 4.



a) Highest b) Lowest

Exhibit 3: Final Wealth Trajectories: Ziemba-Hausch (1986) Model.
Source: MacLean, Thorp, Zhao and Ziemba (2011)

Statistic	1.0k	0.75k	0.50k	0.25k	0.125k
Max	318854673	4370619	1117424	27067	6330
Mean	524195	70991	19005	4339	2072
Min	4	56	111	513	587
St. Dev.	8033178	242313	41289	2951	650
Skewness	35	11	13	2	1
Kurtosis	1299	155	278	9	2
$>5\times10$	1981	2000	2000	2000	2000
10^2	1965	1996	2000	2000	2000
$>5\times10^2$	1854	1936	1985	2000	2000
$>10^3$	1752	1855	1930	1957	1978
$>10^4$	1175	1185	912	104	0
$>10^5$	479	284	50	0	0
$>10^6$	111	17	1	0	0

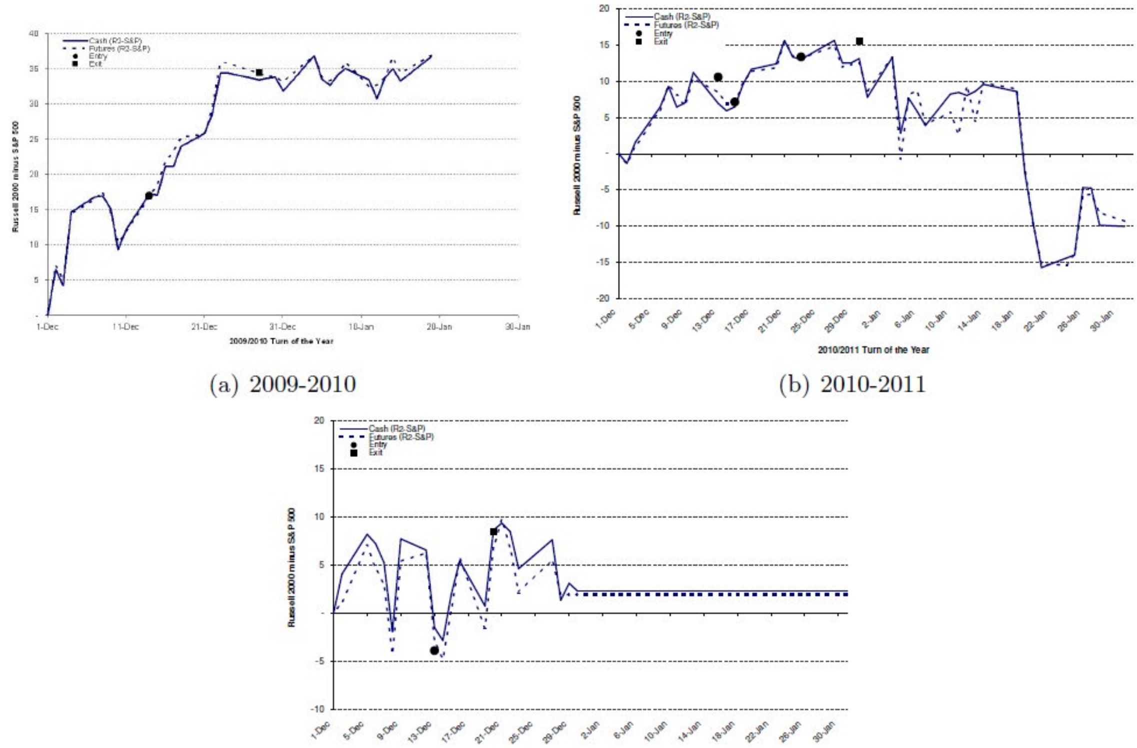
Exhibit 4: Final Wealth Statistics by Kelly Fraction: Ziemba-Hausch (1986) Model Kelly Fraction
Source: MacLean, Thorp, Zhao and Ziemba (2011)

There is a chance of loss (final wealth is less than the initial $1,000) in all cases, even with 700 independent bets each with an edge of 14%.

If capital is infinitely divisible and there is no leveraging, then the Kelly bettor cannot go bankrupt since one never bets everything (unless the probability of losing anything at all is zero and the probability of winning is positive). If capital is discrete, then presumably Kelly bets are rounded down to avoid overbetting, in which case, at least one unit is never bet. Hence, the worst case with Kelly is to be reduced to one unit, at which point betting stops. Since fractional Kelly bets less, the result follows for all such strategies. For levered wagers, that is, betting more than one's wealth with borrowed money, the investor can lose much more than their initial wealth and become bankrupt.

Selected Applications

In this section, I focus on various applications of Kelly investing starting with an application of mine. This involves trading the turn-of-the-year effect using futures in the stock market. The first paper on that was Clark and Ziemba (1988) and because of the huge advantage at the time suggested a large full Kelly wager approaching 75% of initial wealth. However, there are risks, transaction costs, margin requirements, and other uncertainties which suggested a lower wager of 25% Kelly. They traded successfully for the years 1982/83 to 1986/87 - the first four years of futures in the TOY; futures in the S&P500 having just begun at that time. I then continued this trade of long small cap minus short large cap measured by the Value Line small cap index and the large cap S&P500 index for ten more years with gains each



(a) 2009-2010 (b) 2010-2011

(c) 2011-2012

Exhibit 5: Russell 2000 - S&P500 Spread with our Entries (Dots) and Exits (Squares)
Source: **S&P500**
The cash market spread is the black line and the dotted line is the futures spread, the one actually traded

year. The plots and tables describing these trades for these 14 years from 1982/83 to 1995/ are in Ziemba (2012).

Exhibit 5 has graphs of investing with the author's money successfully in December 2009, 2010, and 2011, where the dots are the entries and the squares are the exits. The size of the position is 15% fractional Kelly. The profit on these trades can be seen in the three December periods in the graph. The January effect still exists in the futures markets, but now is totally in December contrary to the statements in most finance books such as Malkiel (2011). The fractional Kelly wager suggested in the much more dangerous market situation now is low. Programmed trading, high frequency trading and other factors add to the complexity, so risk must be lowered as one sees in the volatile 2011/12 graph.

These turn of the year bets are large, however, the Kelly wagers can be very small even with a large edge if the probability of winning is low. An example is betting on unpopular numbers in lotto games. MacLean, Ziemba, and Blazenko (1992) show that with an 82.7% edge, the full Kelly wager is only 65 $1 tickets per $10 million of one's fortune. This is because most of the edge is in very low probability of winning the Jackpot and second prize. While there is a substantial edge, the chance of winning a substantial amount is small and indeed to have a high probability of a large gain requires a very long time, in the millions of years.

Kelly investing has several characteristics. It is not diversified but instead places large bets on the few very best assets. Hence, given the large bets, the portfolio can have considerable monthly losses. But the long run growth of wealth is usually high.

So, How Much Should You Bet?

The optimal Kelly bet is 97.5% of wealth and half Kelly is 38.75%. Obviously an investor might choose to go lower, to 10%, for example. While this seems quite conservative, other investment opportunities, miscalculation of probabilities, risk tolerance, possible short run losses, bad scenario *Black Swan* events, price pressures, buying in and exiting sometimes suggest that a bet much lower than 97.5% would be appropriate. Of course there are also many ways to blow up; see Ziemba and Ziemba (2013) for discussions of several hedge fund disasters, including Long Term Capital Management, Amarath, and Societe Generale.

However, impressive gains are possible with careful risk management. During an interview in the Wall Street Journal (March 22-23, 2008) Bill Gross and Ed Thorp discussed turbulence in the markets, hedge funds, and risk management. Bill noted that after he read Ed's classic *Beat the Dealer* in 1966, he ventured to Las Vegas to see if he could also beat blackjack. Just as Ed had done earlier, he sized his bets in proportion to his advantage, following the Kelly Criterion as described in the book, and he ran his $200 bankroll up to $10,000 over the summer. Bill ultimately wound up managing risk for Pacific Investment Management Company's (PIMCO) investment pool of almost $1 trillion and stated that he was still applying lessons he had learned from the Kelly Criterion: "Here at PIMCO it doesn't matter how much you have, whether it's $200 or $1 trillion. Professional blackjack is being played in this trading room from the standpoint of risk management and that is a big part of our success."

Conclusions

The Kelly capital growth strategy has been used successfully by many investors and speculators during the past fifty years. In this article I have described its main advantages, namely its superiority in producing long run maximum wealth from a sequence of favorable investments. The seminal application is to an investment situation that has many repeated similar bets over a long time horizon. In all cases one must have a winning system that is one with a positive expectation. Then the Kelly and fractional Kelly strategies (those with less long run growth but more security) provide a superior bet sizing strategy. The mathematical properties prove maximum asymptotic long run growth. But in the short term there can be high volatility.

However, the basic criticisms of the Kelly approach are largely concerned with over betting, the major culprit of hedge fund and bank trading disasters. Fractional Kelly strategies reduce the risk from large positions but then usually end up with lower final wealth. If properly used, the Kelly strategy can provide a superior long-term wealth maximizing technique.

Note

This article is a short version of a longer article entitled, "Understanding Using The Kelly Capital Growth Investment Strategy"

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Dr William T. Ziemba is the Alumni Professor (Emeritus) of Financial Modeling and Stochastic Optimization in the Sauder School of Business, University of British Columbia, where he taught from 1968-2006. His PhD is from the University of California, Berkeley. He has been a visiting professor at Cambridge, Oxford, London School of Economics, Stanford, UCLA, Berkeley, MIT, University of Washington, and Chicago among other universities in the U.S. and abroad. Bill has published widely in journals such as Operations Research, Management Science, American Economic Review, Journal of Finance, Quantitative Finance, Journal of Portfolio Management, and Journal of Banking and Finance, as well as in many other journals and special issues. He has contributed regular columns to Wilmott magazine, with his daughter, Rachel Ziemba. His recent books include Handbook of Futures with Tassos Mallarias (2015), Scenarios for Risk Management and Global Investment Strategies with Rachel Ziemba (2007), Handbook of Investments: Sports and Lottery Betting Markets, with Donald Hausch (2008), Optimizing the Aging, Retirement and Pensions Dilemma with Marida Bertocchi and Sandra Schwartz, The Kelly Capital Growth Investment Criterion (2010), with Edward Thorp and Leonard MacLean, and Handbook of Futures with Tassos Mallarias (2015). In progress is a book on the Economics of Wine, with O. Ashenfelter, O. Gergaud.

Hedge Fund Investing: A Conversation with Kevin Mirabile

Barbara J. Mack
Content Director
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Introduction

Kevin Mirabile is a clinical assistant professor of finance at the Gabelli School of Business, Fordham University, where he teaches courses on the principles of finance, alternative investing and hedge funds. Professor Mirabile has enjoyed a long career spanning the investment industry and academia, with a focus on hedge funds and alternatives. He is also on author of a book on hedge fund investing. His book, Hedge Fund Investing: A Practical Guide to Investor Motivation, Manager Profits and Fund Performance, was originally published by Wiley Press in 2013 and is now in its second edition (2016). CAIA had a chance to speak with Professor Mirabile this summer about his perspective on hedge funds, where the jobs are for young people, and how the CAIA program fits in to the picture at Fordham.

How did you get started in alternative investments and what was your career path leading up to your teaching position at Fordham?

I started my career as a graduate from SUNY –Albany with a degree in accounting and economics. I went into public accounting with Arthur Andersen and quickly began to work on assignments in financial services clients. This was in 1983 and much of the work focused on small limited partnerships. At the time, they were not necessarily calling themselves hedge funds or private equity funds; they were simply part of the investment management practice.

After spending a few years at Arthur Andersen, I moved to Morgan Stanley and started a career in capital markets that lasted for almost for 25 years, with several prominent firms and job responsibilities ranging from sales and trading to financial control and risk management. Ultimately I developed products and services for the hedge fund sector. After Morgan Stanley, I went to Daiwa Securities and then sold that business to Barclays Capital and spent seven years there, running many of their balance sheet businesses and some of their listed derivatives, as well as their global prime brokerage business. Throughout this time, I continued to focus on servicing the hedge fund sector and was very fortunate to see the hedge fund industry go from nascent stages in the mid to late 1980s to its peak of over $3 trillion of assets under management in 2015.

After this long stint as a practitioner, I returned to school and obtained a Masters in international banking and finance and a Doctorate in finance and economics and began my teaching career. I became a full time member of the faculty at Fordham University in 2011, after spending several years running a hedge fund and fund of funds business while I was in school. I have been at Fordham ever since then.

For the students that you are teaching at Fordham now, what are some of the challenges they face in the financial world these days?

For students who want to understand hedge fund investing, it is important to develop a very strong baseline in securities investments and analysis, as well as market microstructure. Not every undergraduate program or even every graduate program offers the kind of deep analysis required to understand the dynamics of short selling, or capital structure arbitrage, or fixed income, or relative value. The students in my program are highly motivated self-starters who are excited by capital markets and securities analysis. I believe that you need to have a love for stocks and bonds first and then a passion for hedge funds can evolve from there.

At a practical level, students need access to data – Bloomberg, Preqin, and other financial and economic databases. They also need to read journals like CAIA's Journal of Alternative Investments. And they have to take advantage of professional networking opportunities. Since we are in New York, we have a wonderful alumni network and, in terms of our student base, there is a lot of sponsorship and interest for supporting education in alts.

However, it's still challenging for students coming in directly from undergraduate programs to get into hedge funds. Many of our students will work on the sell side first for a number of years in sales and trading, covering hedge funds, or in investment banking providing leverage to private equity firms – LBOs or MBOs. Over the course of their careers, they will navigate to positions in private equity and hedge funds. Many of these firms are boutiques and the young professionals need the underlying training that can be done by the sell side institutions before they join the alternative firms. This has been changing to a certain extent, as some of the large sell side firms have been cutting back and don't provide the level of education and training that they once did. So I am starting to see some firms hiring directly out of undergrad, but we often tell students these are a destination and it's a goal to end up in a hedge fund or other alternative investment environment; it may not happen right away.

Since you have had a long career and participated in many aspects of the investment business, what do you see as some of the major challenges in the industry now?

I just came back from a training course that I offered to institutional clients in US that covered this topic and it is a timely question. The hedge fund industry, like some of the other investment categories, but perhaps more so, is suffering from a number of challenges.

First, let's look at performance and performance expectations. Since the financial crisis, hedge funds have been underperforming, on an absolute basis, the almost 200% return that we have seen from the S&P 500 since 2008. All too often investors hold hedge funds accountable to nearly matching those types of returns, even though that is misguided, because hedge funds typically have a lot less risk than the S&P 500 – they have much lower annualized volatility, and you would expect them to have a lower return. Having said that, there have been a number of high profile exits – Calpers and NY State Pension fund, for example, have elected to close their hedge fund programs, largely due to the high fees and perceived underperformance.

This generation of hedge fund managers will have to explain, manage, and anticipate investor expectations and be sure that they are delivering what their investors want. In many cases, investors want absolute return, not relative return and then the level of absolute return becomes the issue. We used to say that hedge funds were expected to deliver 80% of equity return with 50% of the volatility – people used the phrase "stock-like return with bond-like volatility." While that is still generally the case, when you have large bull markets like 2013 and a 30% return from the stock market, you should not expect that hedge funds would perform at that level while keeping volatility muted.

Hedge funds have also experienced a number of unusual interventions over the past decade, like the Federal Reserve and central banks being involved in QE1, 2, and 3. A lot of the ability to identify the trends and leverage those trends that we used to see in global macro and CTA funds is diminished when you have government and central bank intervention, and that can change on a dime. For example, this spring we were looking at a June rate rise and now that has been pushed out to September or December, or maybe not at all. You have a lot of unanticipatable regulatory and central bank action that makes it that much more difficult for trend following funds to make a profit.

Even firms that are oriented towards credit or fixed income relative value have ben affected. When credit spreads are low, narrow, and stable, it is very hard to make money on volatility. And even up until to Brexit, the equity market volatilities were relatively low compared to history. So there have been a lot of headwinds against the hedge fund community as firms are trying to capture profits. Going forward, some of those headwinds may become tailwinds, but this has been the biggest issue in recent years.

The second major challenge is related to scalability and infrastructure issues. Hedge funds have gotten bigger faster and now 80% of the assets under managements are managed by funds with greater than $5 billion. Using rough numbers, the top 300-500 firms out of 10,000 control 60-70% of the AUM. So if you are not one of these very large firms, you will still be dealing with higher regulatory costs, higher compliance costs, better due diligence, and a need for improved infrastructure – all of that is expensive. This means there are economies of scale that the

Bridgewaters and Brevan Howards of the world have that the small managers with $100 million doesn't have, even though they will be held to the same standard in terms of creating institutional quality infrastructure. So scalable infrastructure is a big issue.

Finally, the third issue that has had a significant impact is the severe contraction of the Fund of Funds industry. At one point FOFs were providing 50% of assets that flowed from individuals and institutions to hedge funds. That is down to about 25% now and this has forced hedge funds to add larger distribution capabilities and figure out the best channels to market their funds. Retail and liquid alts are a big growth channel, but many hedge funds are not set up to offer '40 Act products. Identifying the appropriate channels and investing in product and business development elements in order to grow their AUM is another important area. This that will offset some of the contraction from the pension funds who have withdrawn, but they have to be successful at accessing new and emerging distribution channels and funding the business development efforts.

What do you think this means for young professionals and how does something like the CAIA designation fit into the picture?

Students of finance are often interested in alternatives, but they need to pursue the education and training proactively. Fordham offers a three-course concentration encompassing private equity, hedge funds, and real estate. This culminates in a capstone course on pan-alternative investments that follows the CAIA Level I curriculum. Students who are enrolled in our program are eligible to receive a scholarship to take the CAIA exam, since we are part of the Academic Partner program, and many students do sit for the exam. This has worked out very well.

In terms of career growth and where the jobs are – areas like collateral management, compliance, risk management have taken on a new level of significance and have to be added in size in many hedge funds. So when we see people obtaining jobs directly out of college, we see that the front office positions –equity research, portfolio management, and trading – are still jobs that require experience, but many of the middle and back office functions, including treasury, collateral management, risk management, securities lending, and technology, are all areas where students and young industry professionals have a lot of opportunities. They may also consider investor relations and client services, where there is a need to explain what funds do and maintain that "high touch" with investors who want to understand what is going on.

Let's turn to your book, since you have covered a vast amount of material on hedge funds there.

Yes, a number of the educational firms have been very interested in the book, including the CFA CAIA FRM and I have been happy with the uptake on this edition. The book was intended to provide a holistic understanding of the hedge fund investment process, so it covers why people invest in hedge funds, what the basic strategies are, and how to perform due diligence on individual fund managers. It is not intended to be a treatise on any one trading strategy, but rather it offers the entry level or recent grad working in the business a big picture view on the hedge fund investing world.

Whether you might be a hedge fund allocator, service provider, or analyst, it is useful to articulate what the structure of the industry is. Readers have said that the book is very useful as a complement to organizations that are in the early stages of allocation of resources to hedge funds. It is a quick way to get up to speed on what is happening in the industry. A lot of financial advisors have also been interested in the book because they are now being held to the suitability standard, so some of the intermediaries that sell hedge funds have to have a deeper understanding to meet their fiduciary responsibilities. I also provide consulting and training to firms who want to learn about the industry and interest has been strong there as well.

Alternatives and hedge funds in particular are something that I love and I was fortunate to have seen some of the early movers and shakers in the industry – David Shaw, Donald Sussman, and Paul Tudor Jones, for example, when they were all just starting out; they were clients of mine and the companies that I worked for, like Morgan Stanley in the late 1980s. So I have had pleasure of seeing business grow from a kind of hobby for high net worth individuals to large-scale institutional firms. Now we even have integrated alternative investment shops too - they may offer private equity, hedge funds, and real estate all under one roof. In this evolution to the mega firm, with companies like KKR and Carlyle, there is a great convergence. It's an exciting time because firms that are single product, single distribution channel are still a boutique offering, but firms that offer multiple products and multiple investor channels are the wave of the future. However, moving from A to B is complex and you need a good strategy to get there. It reminds me of the time when traditional fund managers went down the path of going global and began incorporating derivatives in to their portfolios. Today you see big organization integrating alternatives into their portfolios – so there are lots of opportunities and challenges for all of us during this new period of change.

Bio

Kevin Mirabile
Professor of Finance
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Professor Kevin Mirabile, CPA, teaches finance at the Gabelli School of Business, Fordham University. He has more than 30 years of business development, regulatory, financing, trading and sales experience in financial services. He has developed a specialty in hedge fund business model risk assessment, including counterparty credit, liquidity and operational risk management.

From 2008 to 2011, he was COO and a member of the investment committee at Larch Lane Advisors. Prior to joining Larch Lane, he was COO of Orca Asset Management, a startup hedge fund and registered investment adviser. Professor Mirabile has held senior executive positions with Morgan Stanley, Daiwa Securities and Barclays Capital related to sales, trading, clearing and financing products, while based in New York, London and Tokyo. He is an author of Hedge Fund Investing: A Practical Guide to Investor Motivation, Manager Profits and Fund Performance (Wiley 2013, 2016). He belongs to the Greenwich Roundtable's Founders Council and is a contributor to its "Best Practices" series. He received his BS in accounting from the SUNY Albany, his MS in banking and finance from Boston University and his DPS in finance and economics from Pace University.

Dynamic Asset Allocation as a Response to the Limitations of Diversification

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Institutional investors have to meet challenging goals—above all, achieving a high return target with limited drawdown risk. Yet in the current environment, reaching that objective has become increasingly difficult. Today's current climate of financial repression has lowered return expectations across asset classes. In this environment, many institutional investors face a difficult challenge: How can they meet their return objectives without exposing themselves to substantial drawdown risk? To reach their goals, investors may need to increase allocations to return-generating growth assets such as equities, but this also increases risk. Analyzing the typical allocations of pension plan sponsors, the implied capital losses for many pension funds may likely exceed their risk budgets, which could put risk/return objectives in jeopardy. By doing this analysis, plans can revisit their approaches by asking thoughtful questions: What is the investment goal? What are the risk constraints? How can the return objective be met while prudently balancing risk? This paper explores how using risk-mitigation strategies based on dynamic asset allocation may provide investors with a smoother journey toward their goals in a cost-effective way. Implementing such a dynamic approach—with its dual objective of enhanced returns and risk mitigation—aligns directly with the investment beliefs of many plan sponsors.

The Potential Benefits of Dynamic Risk Mitigation

Many risk-management approaches plans commonly employed, including diversification and tail-risk hedging, have major drawbacks. As a result, dynamic asset allocation (DAA) is becoming an increasingly popular technique for achieving plan-level investment goals within the specified risk budget—an approach called "dynamic risk mitigation." By shifting between risk-seeking growth assets and defensive assets, dynamic risk mitigation may help plans meet or exceed long-term return expectations while minimizing expected drawdown—a philosophy closely aligned with long-term benefit funding and low, stable contribution requirements. Successful design and implementation of dynamic risk mitigation is more demanding relative to other strategies, however its impact on the risk/return profile of the portfolio may also be more rewarding. In the remainder of this paper, we compare commonly used risk-management strategies to dynamic risk mitigation and quantify the benefits of implementing dynamic risk mitigation into a hypothetical pension plan.

Start by Defining The Right Risk Budget

Constructing an investment portfolio and managing it to a specified risk budget are crucial parts of the fiduciary process shared by both staff and fund trustees. Tracking error and standard deviation are abstract ways of quantifying risk that do not communicate true downside-risk potential. Expected dollar loss in an extreme negative market— measured by Value at Risk (VaR) and Conditional Value at Risk (CVaR)—may be more instructive.

As risk can be defined in many ways, a risk budget can be defined by many measures. In general, there are two common methods for defining a risk budget:

- In relative terms versus a benchmark; or
- In absolute terms, measuring the potential change in asset value

The first method measures a portfolio's deviation from its benchmark and is typically expressed as tracking error. Here, risk is not defined in terms of declining portfolio value, but rather as deviating from or trailing its benchmark. While managing an institutional portfolio within a tracking error budget should control large deviations and offer reassurance for the plan's administrators, it does not communicate true downside-risk potential.

In contrast, the second method—the absolute risk-budgeting approach—measures risk in the form of a change in asset value (or funded ratio, in the case of an asset-liability view) and is typically expressed as standard deviation (i.e., volatility). However, standard deviation can only measure the overall dispersion of possible portfolio returns, and it treats positive and negative dispersions equally.

While tracking error and standard deviation are useful—which is clearly why they are the two most popular metrics for measuring risk—they do not easily communicate the true downside risk potential of a portfolio. Instead, defining risk budget as the expected dollar loss in an extreme negative market may be more instructive for decision-makers and stakeholders. This can be assessed with two metrics:

- Value at risk (VaR), which describes the expected loss at a certain point of market severity; and
- Conditional value at risk (CVaR), which states average losses when a specified negative event actually occurs.

Exhibit 1 displays the allocation profile and realized risk/return analytics for a hypothetical public plan (PF A) next to two alternative portfolio allocations (PF B and PF C) based on monthly historical index returns between 2000 and 2015. The plan's profile is consistent with the profile of a public plan typically found in today's investment environment:

- Allocation is 60% global equities and 40% US fixed income
- Annualized beta return of 5.23%
- Standard deviation of 9.63%
- 96.5% of the portfolio's 9.63% total risk (volatility) emanates from the public-equity allocation

A close analysis of the VaR and CVaR shown in Exhibit 1 provides detailed information about the loss potential of such a portfolio:

- The one-year VaR at 95% confidence, based on rolling one-year returns amounts to –14.92%. In other words, a fully funded $1 billion fund might expect to lose at least $149.2 million 5% of the time
- The average loss when such an event occurred was 24.5% (one-year CVaR at 95% confidence). This corresponds to a $245 million loss for a $1 billion fund—or a drop of 24.5 percentage points of funded status (assuming a fully funded plan)

With these experiences in mind, what can plan sponsors do to participate in the return potential of risky assets while limiting loss during falling markets?

Diversification is Important but not Sufficient

As one can observe in the prior table, diversification can improve a portfolio's risk/return profile; however, it does not eliminate the need to manage drawdown risk, which to a large degree arises from the equity-risk contribution. Institutional portfolios typically include many asset classes and are well diversified. Yet diversification largely failed in 2008, as asset classes moved in sync, and did not deliver the benefits sponsors expected as risk within these portfolios was not "diversified." In the asset allocation previously discussed, which includes a public equity allocation of 60%, the asset class drives 96.5% of total portfolio risk.

In Pursuit of Greater Diversification

To address both this equity-risk concentration and to lower overall expected risk, institutions accelerated the search for asset diversification. Alternative investments like hedge funds and private equities were the clear beneficiaries of this movement, although increasing exposure to alternatives comes at a price. One issue is the effect on a portfolio's return profile. On average, hedge funds cannot be expected to yield returns as high as equities. Instead, shifting assets from public equities into private equities in order to capture the illiquidity premium can help to maintain or improve the return level of the portfolio while reducing the overall risk as measured by the standard deviation.

Granted, a 10% inclusion of hedge funds and private equity, pro-rata-funded by 4% of the fixed income and by 6% from the equity allocation can, in fact, improve the portfolio's risk adjusted return. Exhibit 1 shows a more diversified hypothetical portfolio (PF B):

- Return increased from 5.23% to 5.45%, while volatility also decreased from 9.63% to 9.29%. As a result, the overall risk/return profile measured by the Sharpe ratio improved from 0.35 to 0.39.

Asset Class	Asset Allocation Weights			Risk Weights		
	PF A	PF B	PF C	PF A	PF B	PF C
Equities	**60%**	**54%**	**48%**	**96.5%**	**90.4%**	**83.4%**
US Large Cap Equities	32%	28.8%	25.6%	44.7%	41.9%	38.6%
International Equities	21%	18.9%	16.8%	37.0%	34.6%	31.9%
Emerging Market Equities	7%	6.3%	5.6%	14.8%	13.9%	12.8%
Fixed Income	**40%**	**36%**	**32%**	**3.5%**	**3.0%**	**2.4%**
US Government Bonds	25%	22.5%	20%	-1.3%	-1.4%	-1.5%
US Corporate Bonds	15%	13.5%	12%	4.8%	4.4%	3.9%
Alternatives	**0%**	**10%**	**20%**	**0%**	**6.6%**	**14.2%**
Private Equity	0%	6%	12%	0%	4.8%	10.4%
Hedge Funds	0%	4%	8%	0%	1.8%	3.8%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Risk & Return Analytics			
	PF A	PF B	PF C
Hypothetical Return (per annum)	5.23%	5.45%	5.68%
Volatility (per annum)	9.63%	9.29%	8.98%
Sharpe Ratio	0.35	0.39	0.43

Value at Risk (1-Year)			
90%-VaR	-7.98%	-8.27%	-8.80%
95%-VaR	-14.92%	-14.76%	-14.58%
99%-VaR	-27.63%	-27.28%	-27.10%

Conditional Value at Risk (1-Year)			
90%-CVaR	-17.62%	-18.04%	-18.47%
95%-CVaR	-24.50%	-24.88%	-25.26%
99%-CVaR	-29.29%	-29.39%	-29.50%

Exhibit 1: Allocation Profile and Realized Risk/Return Analytics of Different Hypothetical Portfolio Allocations
Source: US Equities Large Cap are represented by the S&P 500 Total Return Index, International Equities by the MSCI Daily TR Gross World Ex US Index, Emerging Market Equities by the MSCI Daily TR Gross EM USD Index, US Government Bonds by the JPM US Treasuries Index, US Corporate Bonds by the Barclays US Corporate Index, Private Equity by the Cambridge Associates US Private Equity Index, Hedge Funds by the HFRI Fund of Funds Composite Index. All calculations are based on monthly returns between 01/2000 and 12/2015.

- One-year VaR marginally changed to -14.76%, while the one-year CVaR actually worsened from -24.50% to -24.88%.

While the average variation of returns, measured by the portfolio standard deviation marginally improved, downside risk, measured by VaR and CVaR was not meaningfully impacted. Further increasing the allocation to alternative assets by doubling its exposure does not change the picture. Exhibit 1 shows this as the third hypothetical allocation (PF C):

- Return increased to 5.68%, while volatility further fell to 8.98% resulting in a higher Sharpe ratio.
- One-year VaR again marginally improved to -14.58% , while the one-year CVaR further dropped to -25.26%.

The main reason these alternative assets classes did not impact downside risk was their lack of diversification in times of market stress. The equity-risk concentration in all three allocation profiles, indicated by the risk weights, is still dominated by public equities. In times of market stress, when correlations among asset classes tend to increase, alternative assets may behave similar to public equities and should not be expected to mitigate the portfolio's downside risk. In fact, the lack of diversification by hedge funds and private equity during the global financial crisis actually led to an increase of "fat tail" risks demonstrated by an increase of the CVaR in PF B and PF C. While alternative asset classes might reduce the average risk measured by portfolio volatility, the downside risk measured by VaR and CVaR were not.

From Static Diversification to Dynamic Diversification

Among more active approaches used to manage the equity-risk contribution, dynamic asset allocation (DAA) strategies distinguish themselves by balancing between downside protection and upside participation. The two significant drawdowns of the past 16 years—the 2000 dot-com collapse and the 2007–2008 financial crisis—have reminded investors that risk management should be a top priority for two main reasons:

- To ensure a smoother ride toward investment goals while experiencing less drawdown risk.
- To gain by not losing and avoid the need to compensate for severe losses, while achieving solid upside participation in strong markets.

Diversification is a critical component of any investment process but, as illustrated above, diversification alone is not sufficient. As a result, many investors have started taking a more active approach to managing downside risk. For example, strategies that address equity tail risk—so-called "tail-risk hedging strategies"—gained attention after 2008, although many sponsors find them ill-suited to long-term allocations. They are expensive and come with a high opportunity cost: buying drawdown protection through put options can easily cost a few percentage points year after year.

Some investors have turned to tactical asset allocation (TAA) to improve the risk/return profile of their portfolios. Like diversification, TAA-strategies can have a positive impact. However, their primary objective is delivering "alpha" rather meeting a return target with minimal risk, which makes them more suitable as an active investment strategy rather than a portfolio-level tool for managing downside.

Dynamic risk mitigation is designed to deliver an asymmetric return profile with the goal of meeting or exceeding the return of the plan's strategic asset allocation in the long run, while minimizing the expected drawdown in the short term. Such a dynamic risk-mitigation approach is strongly aligned with the overall plan-level objectives and therefore suitable for larger scale implementation. To achieve both of the desired goals of a typical institutional investor—drawdown protection and upside participation—an efficient use of DAA must simultaneously target two dimensions: the return relative to the strategic asset allocation (SAA) benchmark and the risk budget. To accomplish this, the DAA-approach needs to capture medium-term trends across asset classes, and combine both pro-cyclical and anti-cyclical components. The use of a well-designed trend or momentum model is an intelligent way to approach active asset allocation. By eliminating the need to forecast future asset-class returns, it is possible to simply position portfolios in light of current market conditions. Within each liquid asset class of the SAA, there are four observable "modes":

- positive trend (normal up-mode);
- negative trend (normal down-mode);
- excessive positive trend (excessive up-mode); and
- excessive negative trend (excessive down-mode).

The four modes are the reflection of behavioral patterns of market participants described by well-researched and prominent asset pricing theories of Barberis, Shleifer, Vishny [1998], Daniel, Hirshleifer, Subrahmanyam [1998] and Hong, Stein [1999]. The response function to these four modes shows both a pro- and anti-cyclical element. With its pro-cyclical element, a DAA-approach can take advantage of the tendency for markets to exhibit trends over time due to the typical under-reaction of market participants. At the same time, market participants occasionally over-react, leading to mean reversion of trends. These reversals can be identified by the systematic anti-cyclical process element. A DAA-approach would reduce the active weight in an asset class as the trend becomes excessively positive, while an excessive negative trend would trigger asset class re-entry to capture the mean-reversion potential.

The dynamic approach employs a portfolio structure based on the plan's strategic asset allocation in order to incorporate the unique market cycles of each sub-asset class that is designed to improve diversification and risk-mitigation potential. For example, if non-US equity is experiencing a negative trend, a DAA-approach may underweight relative to the strategic allocation. The dynamic approach seeks to capture the risk premia of a policy benchmark while also actively managing exposures when markets are under stress as a way to mitigate downside risks.

Dynamic Asset Allocation in Action

We are able to illustrate this concept using the global 60/40 strategic asset allocation outlined in Exhibit 1 (PF A) and a rules-based simulation setup outlined in Exhibit 2. The table illustrates the asset classes, the SAA weights, their minimum and maximum weights in the simulation, and the index used. The simulation results are gross of management fees and net of transaction costs. Equity is the main risk-contributing asset class; therefore, risk mitigation occurs by cutting the weight from 60% potentially down to 20%, while return enhancement is made possible by increasing the weight from 60% potentially up to 80%.

The 2:1 ratio between the de-risk range and up-risk range reflects the intended asymmetric return profile. These guidelines will ultimately determine the level of expected excess return, drawdown and tracking error; as such, understanding how these measures interact is vital to setting appropriate expectations.

The benefit of dynamic asset allocation is apparent in both absolute and relative risk-return measures. In the comparison shown in Exhibit 3, the dynamic approach could have added 234 basis points (bps) of annualized excess return for 373 bps annualized tracking error, an information ratio of 0.63 and a meaningful improvement in Sharpe ratio. While comparing the annualized volatility of DAA with SAA (8.53% vs. 9.63%), both approaches indicate a rather similar risk profile. The true impact of DAA becomes apparent when comparing downside risk figures VaR and CVaR. Furthermore, going beyond VaR and CVaR by simply comparing the worst realized 12-month returns, DAA delivered risk mitigation with approximately one-third less downside.

While comparing typical performance and risk analytics of the DAA-approach vs. the strategic asset allocation, one might conclude the outperformance of 2.34% is mainly due to risk mitigation. Further insight into the outperformance pattern and its persistency give the below two graphical evaluations.

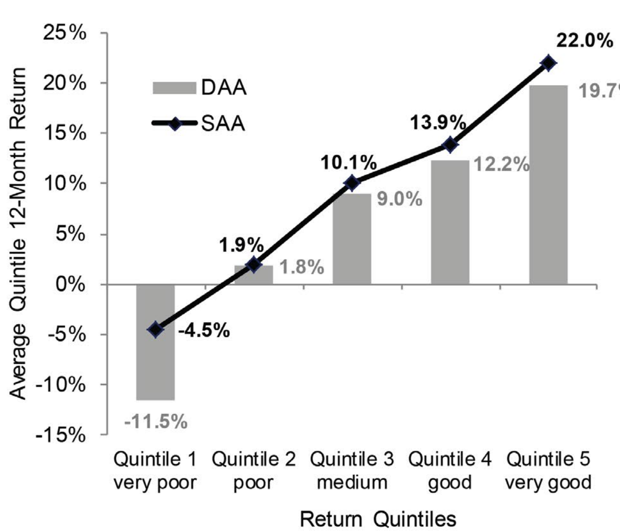
The left chart of exhibit 4 uses a technique of Fung, Hsieh [1997], segmenting the rolling 12-month average SAA returns into quintiles and comparing average returns with the DAA-strategy returns in these quintiles allows for a more robust return comparison over five different market environments. Based on the average quintile returns, the DAA-strategy yields outperformance on average in all five quintiles. This aggregated

Asset Class	SAA	Min	Max	Index Used for Simulation
Equities	**60%**	**10%**	**80%**	
US Equities Large cap	30%	10%	65%	S&P 500 Total Return Index
International Equities	21%	5%	35%	MSCI Daily TR Gross World Ex US Index
Emerging Market Equities	7%	0%	15%	MSCI Daily TR Gross EM USD Index
Fixed Income	**40%**	**20%**	**80%**	
US Government Bonds	25%	10%	80%	JPM US Treasuries Index
US Corporate Bonds	15%	0%	40%	Barclays US Corporate Index
Oppurtunistic Assets	**0%**	**0%**	**20%**	
US REITs	0%	0%	10%	FTSE E/N All Equity REIT Total Return Index
Commodities	0%	0%	10%	Bloomberg Commodity Total Return Index
US Equities Small Cap	0%	0%	10%	Russell 2000 Total Return Index
Emerging Market Debt	0%	0%	10%	JPM Emerging Markets Bond Index
US High Yield	0%	0%	10%	iBoxx LiquidHigh Yield Index
US TIPS	0%	0%	10%	Barclays US Treasuries Inflation Linked Index
Cash	**0%**	**0%**	**60%**	

Exhibit 2: Simulation Parameters for a Hypothetical DAA Portfolio Between 01/2001 and 12/2015
Source: Allianz Global Investors

Absolute Performance & Risk	DAA	SAA
Hypothetical Return (per annum)	7.57%	5.23%
Volatility (per annum)	8.53%	9.63%
Sharpe Ratio	0.67	0.35
95%-VaR	-6.27%	-14.92%
95%-CVaR	-15.13	-24.50%
Minimum 12-month return	-20.98%	-30.83%
Relative Performance & Risk		
Hypothetical Outperformance (per annum)		2.34%
Tracking Error (per annum)		3.73%
Information Ratio		0.63

Exhibit 3: Analytical Simulation Results of Historical Backtest
Source: Allianz Global Investors



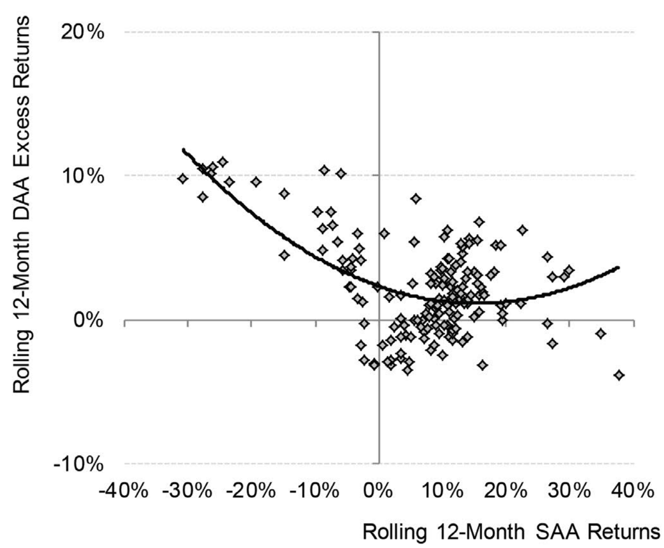


Exhibit 4: Comparing Return Outcomes of a Hypothetical DAA Portfolio Relative to SAA
Source: Allianz Global Investors

relative performance pattern reflects the objective of the DAA-approach: providing outperformance due to risk mitigation in sustainable negative markets and return enhancement in positive trending markets. By design, the degree of outperformance is greater in negative SAA-return scenarios due to the asymmetric asset class ranges, de-risking the equity exposure twice as much as up-risking. What is the trade-off for receiving the aggregated outperformance pattern outlined in the quintile chart? The investor must be willing to accept dispersion of short-term active returns including periods where the strategy lags its static reference benchmark, as indicated by 3.73% tracking error. Following Moskowitz, Ooi, Pedersen [2012], the scatterplot of all 168 rolling 12-month DAA excess returns is illustrated in the right chart of Exhibit 4, visualizing a momentum smile effect. Here, the strategy underperformed in 44 periods, typically during volatile sideways-equity markets with weak or no clear trend where the active allocation strategy accrues volatility costs. Both the quintile chart and the momentum smile reflect the desired convex payoff profile or skewed smile: due to the asymmetric allocation leeway, the DAA-approach is aiming for a stronger degree of risk mitigation in severe down markets than the correspondent degree of return enhancement in the same size substantial up markets.

How to Make Static Portfolios Dynamic

In order to take full advantage of the DAA-approach when integrating it into a strategic allocation, plan sponsors should consider a total-portfolio view toward sizing the dynamic asset allocation and analyzing its impact. An investor can blend the dynamic allocation into the overall portfolio to create an asymmetric return profile for the total plan. By starting from the SAA weights, the dynamic approach targets at least the expected plan return while ensuring that short-term return deviations (tracking error) remain limited.

The first step involves carving out an equivalent proportion of liquid assets within the SAA, such that the remainder still reflects the composition of the SAA. The second step invests these assets using the dynamic approach, and the third step blends the dynamic segment back into the overall portfolio to observe its impact. To determine the most efficient size for the dynamic allocation segment, the dynamic allocation may be calibrated to achieve a specific outcome, or it may be driven by a statistical constraint. An outcome-oriented approach targets the degree of desired return enhancement or drawdown mitigation compared with the policy benchmark. A statistical constraint might define overall asset-class deviation versus the policy benchmark, or the tracking error compared to the current rebalancing policy. Exhibit 5 illustrates various blends between a DAA-approach and an SAA-based policy portfolio.

An outcome-oriented approach to finding the appropriate size for active allocation within an overall portfolio begins with quantifying the expected compound return and return distribution of the policy benchmark. Due to the equity risk concentration and large drawdown potential in most client portfolios, risk mitigation is generally the target outcome. To that end, it is important to note that dynamic asset allocation's asymmetric return compared with a plan sponsor's benchmark can enable risk mitigation without sacrificing the long-term expected return—the unpleasant tradeoff typically required of other risk-mitigating concepts. With the previously specified DAA-approach, the 2:1 de-risk to up-risk ratio means risk mitigation's positive effects on a total plan could accrue at a faster rate than return enhancement, as seen in Exhibit 5. In this backtested scenario, a 10% allocation to dynamic allocation improved the worst 12-month return by 0.95% while improving the long-term assumed return from 5.23% to 5.56%. As the example shows, an allocation to the DAA-approach linearly indicates both effects: short-term drawdown reduction and long-term return enhancement.

Absolute Analytics	SAA	DAA	10% Blend	20% Blend	30% Blend	40% Blend
Hypothetical Return (per annum)	5.23%	7.57%	5.46%	5.69%	5.93%	6.16%
Volatility (per annum)	9.63%	8.53%	9.46%	9.31%	9.16%	9.03%
Sharpe Ratio	0..35	0.67	0.38	0.41	0.45	0.48
Minimum 12-month return	-30.83%	-20.98%	-29.88%	-28.93%	-27.96%	-26.99
Relative Analytics						
Hypothetical Outperformance (per annum)		2.34%	0.23%	0.47%	0.70%	0.94%
Tracking Error (per annum)		3.73%	0.37%	0.75%	1.12%	1.49%

Exhibit 5: Blending Dynamic into Static and its Impacts on the Portfolio
Source: Allianz Global Investors

How to Size the Dynamic Slice

Clearly, despite the long-term horizon of institutional investors, minimizing short-term drawdown in such a way has merit for a variety of reasons—including peer-relative comparisons, board/staff evaluation periods and managing a negative cash flow portfolio. As a result, a plan sponsor seeking to reduce a portfolio's expected drawdown, or seeking to identify a new source of return without adding volatility, may use the sensitivity data shown in Exhibit 6 to target specific outcomes.

The most intuitive statistical method for targeting these outcomes simply uses deviations in asset allocation compared with the policy benchmark. Blending different percentages of the dynamic asset allocation strategy with a static benchmark creates an implied asset-class-deviation table. For example, using the dynamic asset ranges described previously, 10% of liquid assets allocated to the dynamic strategy realizes only 10% of its total impact. The dynamic asset ranges allow an up-risking by 20 percentage points and de-risking by 40 percentage points around the strategic equity exposure of 60%, therefore a 10% allocation

Rebalancing Policy		Dynamic Blend		Implied Equity Ranges	
Asset Class Range	Tracking Error	Weight	Tracking Error	Up	Down
2.5%	0.42%	10%	0.37%	+2%	-4%
5.0%	**0.84%**	**20%**	**0.74%**	**+4%**	**-8%**
7.5%	1.26%	30%	1.11%	+6%	-12%
10.0%	1.68%	40%	1.48%	+8%	-16%

Exhibit 6: Designing the Hypothetical Blend Between the Static and Dynamic Portions of the SAA
Source: Allianz Global Investors

translates into 10% of this dynamic allocation range, i.e., +2% and -4% maximum asset-class ranges in the overall portfolio. For many plans, these are within the range of a rebalancing policy, so implementation would require limited policy-level considerations.

Another statistical approach to finding the appropriate size for dynamic allocation examines the tracking error that dynamic exposure would introduce. The rebalancing policy or active risk budget defines the acceptable drift from policy weights, which equates to an implicit tracking error. This active risk is typically unaddressed by active management and, therefore, most portfolio-level tracking error is not compensated with expected excess return or risk mitigation. Using dynamic asset allocation could redeploy this unused active risk budget for both return enhancement and risk mitigation in order to potentially improve the overall portfolio.

An example of how to redeploy unused active risk budget by staying within tracking-error ranges can be seen in Exhibit 6. It compares the implicit tracking-error budget of rebalancing policy equity ranges with the corresponding dynamic exposure weight producing similar tracking error. A rebalancing policy allowing a +/- 5% equity range means that a plan can expect 0.84% tracking error relative to its policy benchmark. Yet equipping a portfolio with a 20% exposure to dynamic allocation stays within this tracking-error-budget as it introduces just 0.74% portfolio-level tracking error. As the tracking error from rebalancing policy and dynamic blend scales linearly with the asset class ranges and dynamic weights respectively, any idle tracking error budget of a rebalancing policy can be employed by implementing the tracking-error equivalent DAA-component.

Clearly, there are different ways to consider the size of a dynamic allocation blend. Whatever decision is made, the larger the allocation to the dynamic asset category, the greater its effects. These effects can be expressed in multiple terms as a function of:

- the degree of desired return enhancement;
- the degree of desired risk mitigation;
- the desired allocation range to be introduced to the static SAA weights; and
- tracking-error-neutral sizing in relation to a portfolio's current rebalancing policy.

Dynamic Asset Allocation as a Toolkit

The objective of delivering excess return while minimizing downside risk aligns with the philosophy statement of most institutional plan sponsors. However, many approaches commonly used to deliver this goal fell short in one dimension. Dynamic asset allocation offers investors a unique toolkit designed to achieving these objectives and potentially improving distribution of plan returns over time. Its customized implementation structure and asset class parameters enable any institution to become dynamic to help more efficiently utilize an existing risk budget to attain the goals of risk mitigation and return enhancement.

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Mr. Zimmerer is a senior product specialist and a director with Allianz Global Investors, which he joined in 2014. As a member of the Multi Asset US team, he is responsible for articulating the philosophy and process of the firm's dynamic multi-asset strategies to clients and external audiences; he also provides insights to the advisor and consultant community on the impact of market conditions on portfolio decisions. Earlier with the firm, Mr. Zimmerer was a portfolio manager with Allianz in Munich and Frankfurt, where he developed quantitative investment strategies and managed bond and CPPI portfolios. He has 19 years of investment-industry experience. Before, Mr. Zimmerer was a professor of finance and investments at the University of Applied Science in Ansbach, Germany, and served as senior consultant for a German-based consulting firm, advising institutional investors. He has an M.B.A. in economics and finance and a Ph.D. in econometrics from the University of Regensburg, Germany.

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Mr. Carrington is a senior relationship manager and a director with Allianz Global Investors, which he joined in 2014. He is responsible for new-business development in the central region of the US. Mr. Carrington has 15 years of investment-industry experience. Before joining the firm, he worked at Janus Capital Group in institutional business development across corporate, endowment and foundation, public and insurance plans. Mr. Carrington also worked in equity research sales with Cowen and Company, where he placed initial and secondary offerings in equity and convertibles, and was responsible for traditional equity research sales to asset managers in the technology, health care, defense/aerospace and media sectors. Before that, he worked at Stifel Nicolaus in equity research sales. Mr. Carrington has a B.A. in economics from Wake Forest University. He is a CFA charterholder.

VC-PE Index

A Look at North American Private Equity as of Q4 2015

Mike Nugent
CEO/Co-Founder
Bison

Mike Roth
Research Manager
Bison

TVPI Momentum

The one-year TVPI momentum (% change in TVPI y-o-y) was relatively modest for the North America All PE and buyout segments. For the vintage years between 2000 – 2012, All PE increased by 1.6% and buyouts increased by 1.9%. Meanwhile, venture capital's TVPI momentum led the way with an average TVPI momentum of 5% for the 2000 – 2012 vintage years.

The chart below digs into the 2005 – 2012 vintage years. These are the vintage years that are in the early to late stages of maturation and, therefore, the most meaningful to analyze.

For the 2005 – 2012 time period, venture capital's one-year TVPI momentum outpaced buyouts in seven of eight vintage years. The strongest vintage years for venture capital over the last year have been 2008, 2011, and 2012.

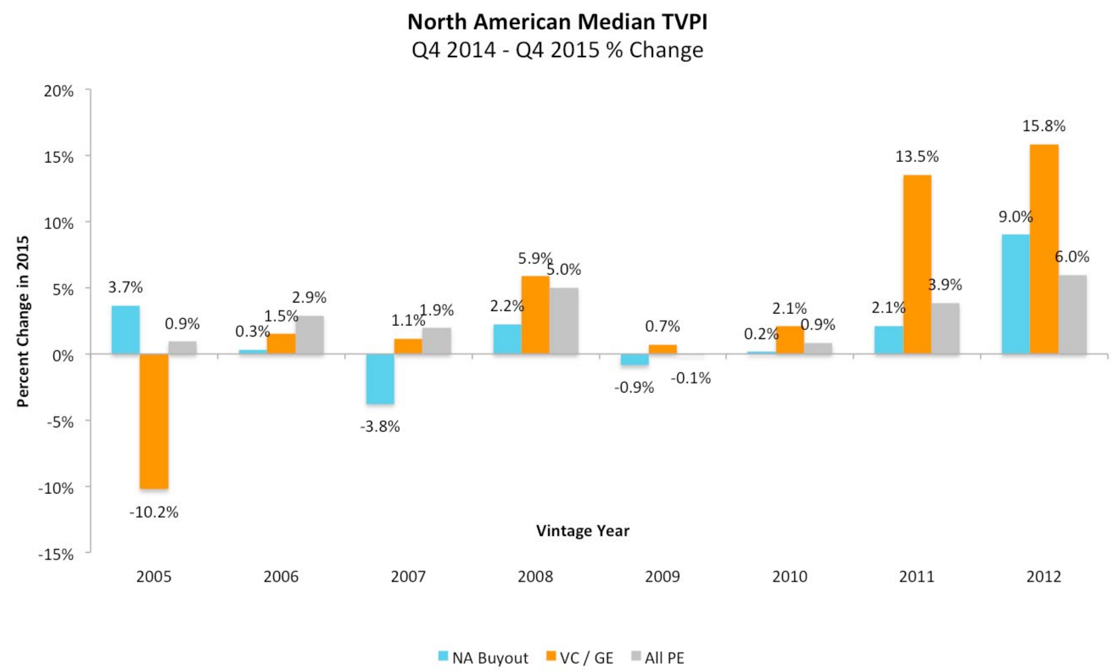

Exhibit 1: North American TVPI
Source: Bison

DPI Momentum

Although TVPI metrics were relatively flat during 2015, private equity firms were busy selling assets, which increased their DPI ratios. The chart below looks at the one-year DPI momentum (% change in DPI y-o-y) for the 2005 – 2012 vintage years.

North America venture capital led the way with an average DPI momentum of 118%. It should be noted that the average is being skewed by extraordinarily high percentage for the 2011 vintage year. If you were to exclude the 2011 vintage year, the average DPI momentum for venture capital would be 43%.

Comparing DPI momentum for venture capital to buyouts tells a mixed story. The DPI momentum for buyouts during this period averaged 63% and they outpaced venture capital in four of the eight vintage years. North American venture capital was busy increasing the value of their assets while North American buyouts were busy realizing the value of their assets.

To learn more about Bison and how we can help you understand private equity performance metrics, please visit www.bison.co.

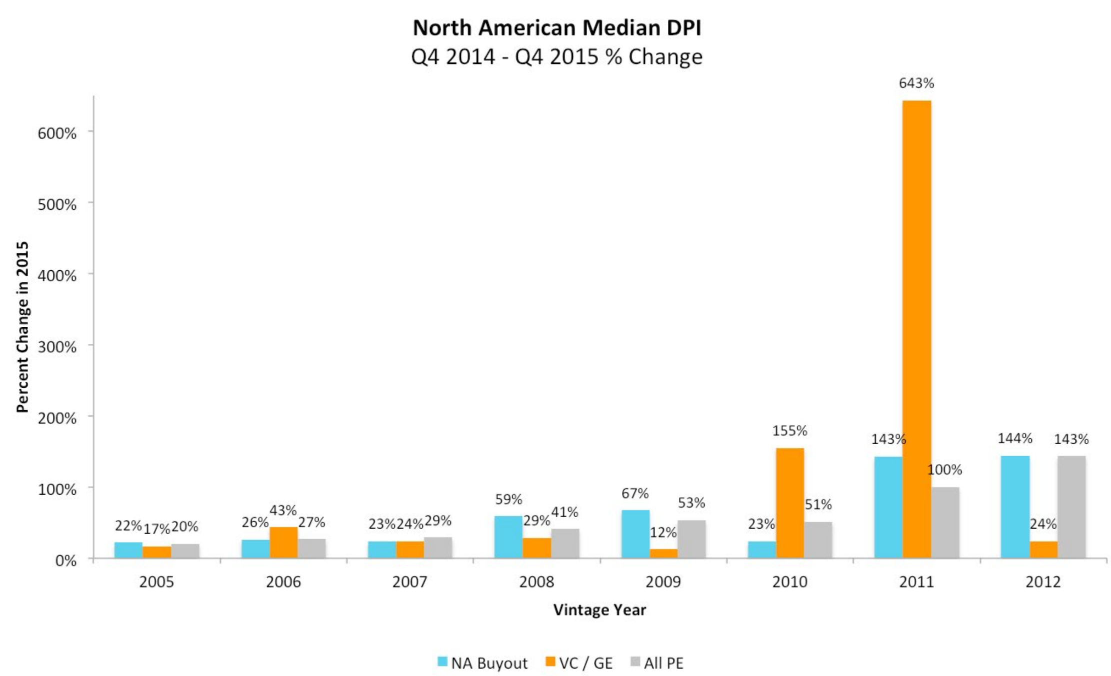

Exhibit 2: North American Median DPI
Source: Bison

Authors' Bios

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CEO/Co-founder, Bison

Prior to founding Bison, Mike Nugent held senior roles at SVG Advisers, LP Capital Advisors and HarbourVest Partners, and has more than $3B in private market commitments to his credit. Mike started his career in the public markets with the NASDAQ Stock Market, and also gained significant operating experience while running operations for a textiles manufacturer. He received his MBA from Boston College, and his BA from St. Bonaventure University. Mike lives on the North Shore of Massachusetts with his wife and two sons.

Mike Roth
Research Manager, Bison

Mike Roth is the Research Manager at Bison and oversees the data collection and content production. Before Bison, Mike spent six years on the investment team at SVG Advisers. There, he conducted research and due diligence on buyout and venture capital funds in the Americas. Mike received his BA in Economics from Boston College and is a CFA Charterholder.

LISTED OR PRIVATE REAL ESTATE?

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Summary

Two roads lead asset owners into real estate: the private (direct and indirect) ownership route and the public equity route. With private assets, investors can analyze performance in detail, down to the asset and vehicle level. However, listed real estate, which includes public Real Estate Investment Trusts (REITs), rarely offers that level of data, making it very difficult for asset owners to monitor a seamlessly integrated portfolio consisting of both private and public assets. This divergence is taking on new importance because of two key developments. First, the upcoming reclassification of real estate in August 2016 into a separate sector within GICS® may draw greater attention and scrutiny to real estate securities. Second, the gradual globalization of the real estate investment market may lead institutional investors to look to international listed real estate as a simpler and often liquid way to diversify their real estate portfolios geographically, rather than purchasing individual properties or holdings in private unlisted funds in various markets.

Listed Real Estate as a Share of the Equity Market

The weight of listed real estate companies within the total equity market has increased considerably in the past 16 years (Exhibit 1). This rising weight, along with lower correlations with other listed financial sector firms, contributed to the decision to move real estate into a separate sector within the GICS classification. Listed real estate's increasing size and market share has been notable in Europe; however, the sector still is relatively small compared to the other regions.

Despite its growing prominence, institutional investors treat listed real estate differently in their asset allocations: Some consider listed property to be part of the real estate allocation while others see it as merely another part of their equity exposure.

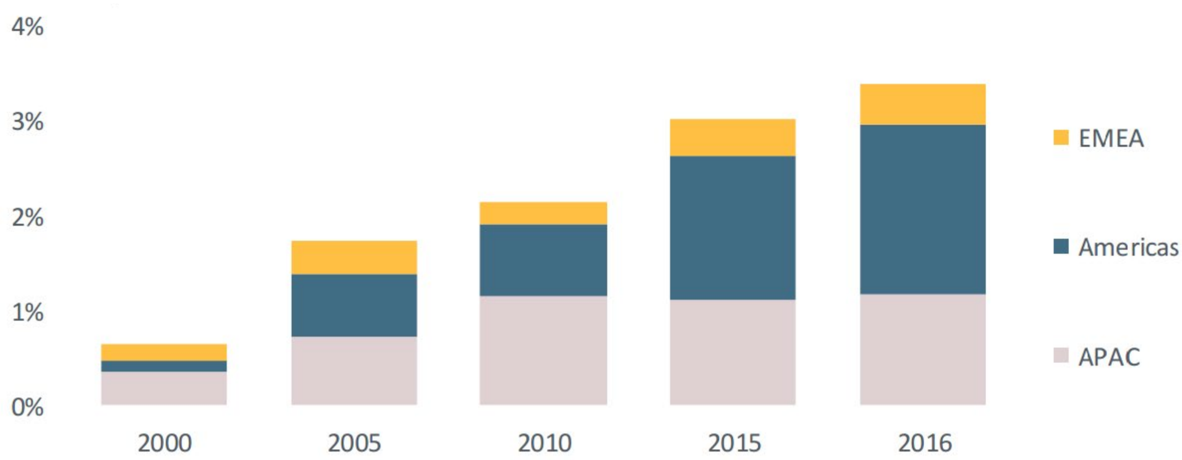

Exhibit 1: Evolving Weight of the Real Estate Industry Group (in ACWI across regions)
Source: MSCI
Weight (% in MSCI ACWI index)

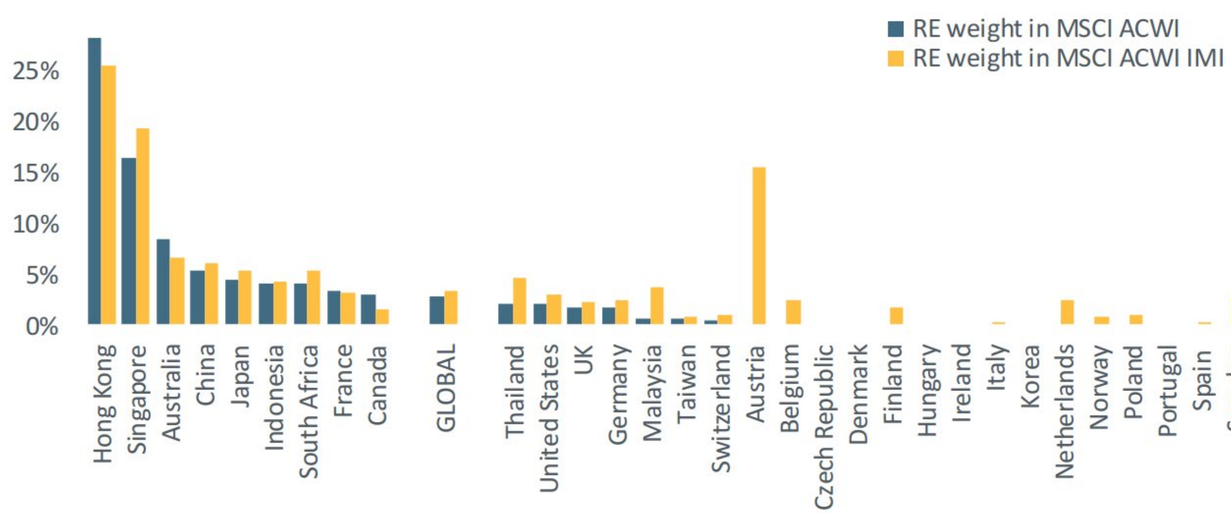

Exhibit 2: Listed Real Estate as a % of Total Equity Indexes, December 2014
Source: MSCI

Exhibit 2 compares listed real estate weights in 31 countries against two global equity indexes, the MSCI ACWI Index and the broader MSCI ACWI Investable Market Index (IMI), as of December 2014. In general, Asian markets held the highest real estate weights, particularly Hong Kong and Singapore; real estate companies in those city-states tended to own significant non-domestic assets, especially in China and other countries in that region. The only European country where listed real estate firms held a weight larger than 5% in one of the two global equity indexes was Austria, due to listed companies having a large nondomestic exposure in Central and Eastern Europe. There were far more real estate companies in the broader MSCI ACWI IMI than in the MSCI ACWI Index, reflecting that these firms generally are smaller than companies in other sectors. As of October 2015, Austria, Belgium, Finland, Italy, Netherlands, Poland, Spain, and Sweden, for example, did not have real estate firms meeting the minimum threshold of $5 billion in market capitalization for inclusion in the MSCI ACWI Index (MSCI, 2016). However, those countries had plenty of smaller companies included in the MSCI ACWI IMI Index.

Listed Real Estate as a Share of the Managed Market

Many institutional investors view listed real estate as part of their overall real estate exposure and thus evaluate those holdings against real estate benchmarks. Thus, comparing listed real estate to the professionally managed real estate market has merit. Exhibit 3 shows listed companies as a proportion of the professionally managed real estate investment market by country. Again, we find that listed companies are significant players in Asia, but much less so in Europe, where the only country for which the proportion of the managed market owned by listed companies exceeds 30% is Sweden. That uneven situation exists because the European market is dominated by relatively large asset owners with direct portfolios, including insurance companies, pension funds, and sovereign wealth funds (SWFs). Unlike Asia, Europe also supports a relatively large unlisted fund sector. Some differences in the data may have a bearing on performance attribution analyses. For example, some countries may appear under-represented in Exhibit 3 because the proportions shown are based on the actual location of the

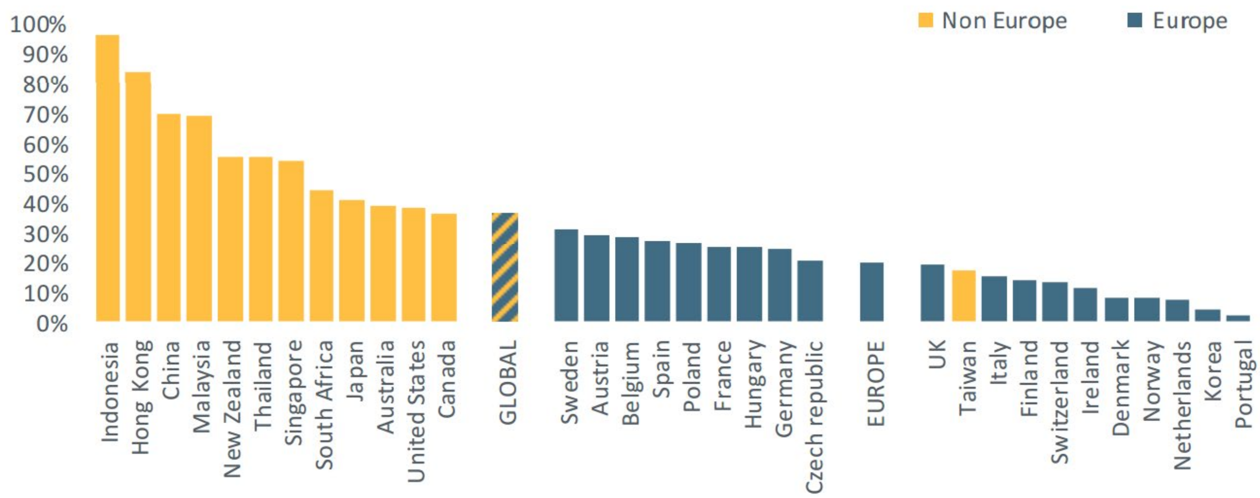

Exhibit 3: Listed Real Estate as a % of Total Professionally Managed Market, 2014
Source: MSCI

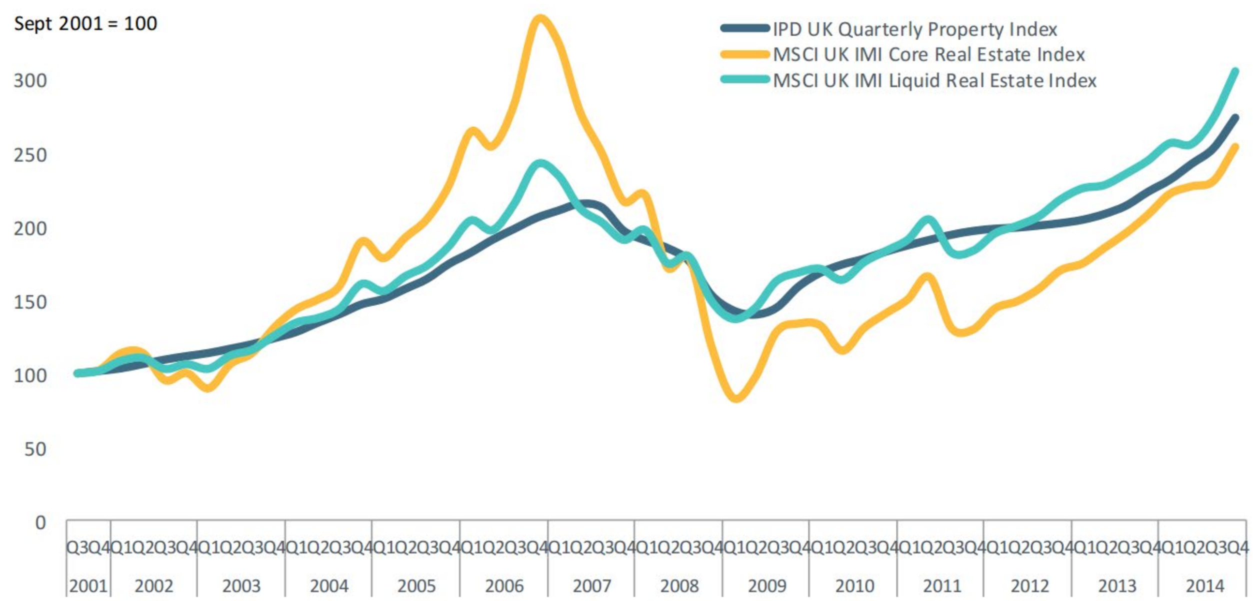

Exhibit 4: Listed vs. Direct Real Estate Performance in the U.K.
Source: MSCI;

assets owned rather than the country of listing for the real estate company, e.g., real estate companies listed in the Netherlands held relatively large proportions of non-domestic investments. At a global level, over 85% of listed real estate holdings are located in the country of listing. In Europe, the average level is only slightly lower (82%). In some countries, such as Germany, Spain, Sweden and Switzerland, the home bias ratio exceeds 95%; in others, such as Austria and the Netherlands, domestic holdings fall below 40%.

The Research Landscape

In theory, an asset owned by a listed company should be indistinguishable in performance from an equivalent privately owned asset. In practice, however, this comparison has been difficult to quantify, as researchers and equity analysts have discovered. One approach to comparing performance between listed and private assets has focused on long versus short time horizons. Share prices of listed companies are affected by volatility in the stock market, while underlying real estate values are subject to infrequent appraisals. As a result, correlations between the listed real estate and direct real estate are relatively low, particularly in short time horizons. The noise and volatility of continuous equity pricing clashes with the smoothed and lagged nature of periodic appraisal valuations. To correct for this, attempts have been made to substitute transaction-based indexes for valuation based indexes in some markets. The more sophisticated the studies become, the higher the correlations between listed and direct performance. Recently, MSCI developed new indexes that mimic the performance of direct real estate by seeking to reduce volatility and deleverage the listed index. This methodology is now applied in the MSCI USA IMI Liquid Real Estate Index and the MSCI UK IMI Liquid Real Estate Index. As can be seen in Exhibit 4, the Liquid Real Estate Index more closely tracked the performance of the IPD® UK Quarterly Property Index (a direct property index) than the MSCI UK IMI Core Real Estate Index (which tracks real estate stocks) during the sample period.

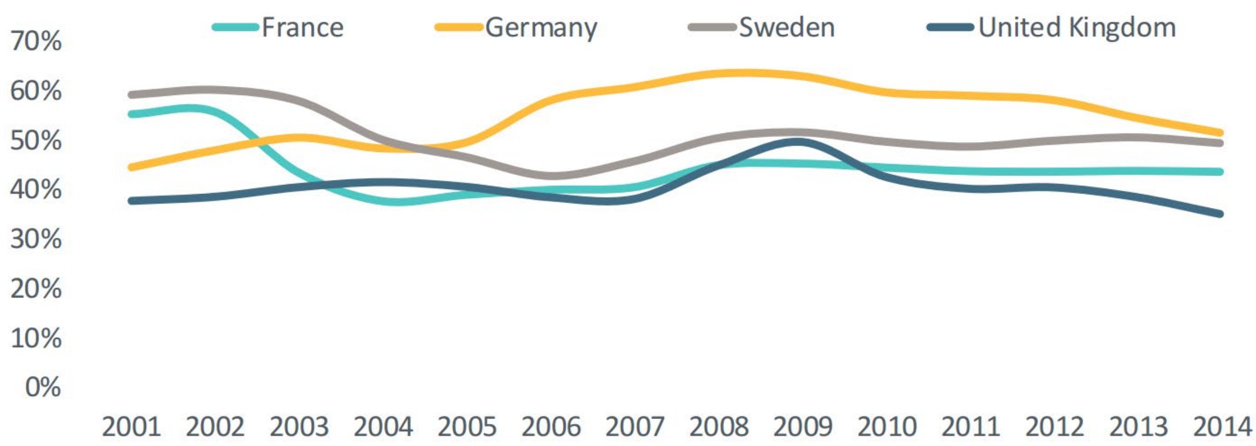

Exhibit 5: Average Loan-to-Value (LTV) Ratio for European Listed Real Estate
Source: MSCI

How Do Corporate Strategies Differ?

The main elements of the real estate strategies related to allocation (property type and geographic focus) and management decisions (leverage and development exposure).

Allocation Decisions

- *PROPERTY TYPE.* Listed real estate companies in the U.S. often diversify across regions, states or metropolitan areas, while focusing on one property type. This approach is less common practice in Europe, though a few listed companies do favor a similar national and sector focus, centering on the retail, office, residential, industrial, healthcare or hotel/resort sectors. The forthcoming GICS classification will follow sector specific classifications, further institutionalizing a sector-specific framework within the listed environment.
- *GEOGRAPHY.* Unlike the U.S., European countries are smaller and more densely populated, prompting many listed companies to opt for geographically focused strategies diversified across property types [Global Securitized Real Estate Benchmarks and Performance, 2009].

Management Decisions

- *LEVERAGE (GEARING).* Leverage can have a huge impact on returns for both direct and listed real estate. While direct real estate performance is measured free of leverage at the asset level, vehicles can have significant leverage. Commingled (unlisted) real estate funds vary in the use of leverage. Funds with a low leverage are referred to as core funds, while those with relatively high leverage are referred to as value add or opportunistic funds. The PREA/IPD U.S. quarterly property fund indexes (produced at the core fund and all-fund levels) show how leverage can have a positive impact on fund returns in periods of cyclical expansion but a negative impact during down cycles. The level of leverage has also produced an overall impact on performance volatility. For European listed real estate, the use of leverage as a strategy varies, with loan to-value ratios ranging from 40% to 65% at a country level (Exhibit 5). Although leverage is one of the main drivers of risk at the vehicle level, few listed European companies incorporated a flexible view on the use of gearing. This lack of flexibility leaves investors potentially vulnerable. Vehicles offered by listed companies may have embedded very different risk levels which can impact performance significantly across the real estate cycle.
- *DEVELOPMENT EXPOSURE.* Active management can range from the cautious, such as a focus on long-term leases, to the speculative, such as greenfield property development. Other strategies, such as active lease-up, refurbishment, privatization of residential units, expansion and redevelopment, lie in the middle of the risk spectrum. Development property garners little space in the balance sheets of listed companies in Europe. Exposure to development averages approximately 5% of total assets, and this ratio differs considerably across countries. Opportunistic development strategies can lead to higher returns, but this is coupled with elevated risks.

Conclusion

The conundrum for investors is that real estate companies tend to provide data at the company (security) level, but relatively few are transparent at the asset (individual property) or vehicle (fund) level. Instead, most listed companies compare their performance to equity market benchmarks. While such benchmarks make sense for passive equity market investors, many institutional investors could benefit from participation of listed real estate companies in established real estate benchmarks. This way, institutional investors could explain the impact on performance of market and property type, show the impact of debt and active management at a vehicle level and isolate and quantify market sentiment.

Dynamics in performance between listed and unlisted real estate has been widely researched from a top-down perspective. Several remedies to close this gap have been proposed, most recently with the birth of the 'liquid real estate index'. Research now needs to shift to a complementary bottom-up approach, focusing on granular attribution analysis and reconciliation across asset, vehicle and security levels. This approach will assist sophisticated investors to better integrate their real estate allocations across multiple asset classes. In short, a solution needs to be mapped that can show quantitatively how much of a listed real estate firm's return is attributable to fundamental property performance at the asset level, how much is contributed by debt and active management decisions at the vehicle level and how much of the remaining performance is explained by market sentiment alone at the security level. In the current environment, asset managers and asset owners lack the fundamental tools needed to analyze their listed real estate portfolios properly. This situation leaves them ill equipped to make strategic and tactical allocation decisions.

The next Global Intel update will lay out a methodology that enables institutional investors to assess exposure across both listed and unlisted real estate. By peeling away market sentiment at the security level and active management decisions at the vehicle level, the underlying performance of the assets — including net operating income (NOI), NOI growth, capital growth, yields and income risk — can all be compared seamlessly and like-for-like across a global portfolio of listed and unlisted holdings.

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Max Arkey works in product management at MSCI Real Estate where he heads up indexes and market information products. These analytics are mission critical to the investment process for 19 of the top 20 largest global asset managers, all the way through to specialized domestic investors.

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