Hedge Funds:
A Dynamic Industry In Transition*

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Abstract

The hedge-fund industry has grown rapidly over the past two decades, offering investors unique investment opportunities that often reflect more complex risk exposures than those of traditional investments. In this article we present a selective review of the recent academic literature on hedge funds as well as updated empirical results for this industry. Our review is written from several distinct perspectives: the investor's, the portfolio manager's, the regulator's, and the academic's. Each of these perspectives offers a different set of insights into the financial system, and the combination provides surprisingly rich implications for the Efficient Markets Hypothesis, investment management, systemic risk, financial regulation, and other aspects of financial theory and practice.

Keywords: Hedge Funds; Alternative Investments; Investment Management; Long/Short; Illiquidity; Financial Crisis.

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1 Introduction

The growth of the hedge-fund industry over the past two decades has been nothing short of miraculous. In 1990, hedge funds managed approximately $39 billion in assets, and despite several industry-wide crises—including the Asian Contagion (1997), Long-Term Capital Management (1998), the bursting of the Tech Bubble (2001–2002), the subprime mortgage crisis (2006–2008), and the ongoing European debt crisis—current estimates put hedge-fund assets at $2.5 trillion. This astonishing rate of growth is not accidental. It reflects a broad and abiding demand for what hedge funds offer: higher risk-adjusted expected returns; greater diversification across assets, markets, and styles; and fewer constraints on portfolio managers who are incentivized to generate unique sources of excess expected returns, i.e., "alpha".

However, along with these advantages, hedge funds also offer more complex risk exposures that vary according to style and market circumstances— risks such as "tail events", illiquidity, and valuation uncertainty. Also, because hedge funds enjoy greater latitude in their investment mandate and typically provide little transparency to their investors because of the proprietary nature of their strategies, the possibility of fraud and operational risks is of much greater concern to their investors. If typical hedge-fund investors are considered "hot money", there may be good reason.

These conflicting characteristics may explain why investors have a love/hate relationship with alternative investments. According to HFR (2013), in 2013Q4 63% of funds of funds experienced fund outflows; however, only 45% of single-fund manager funds did. This is consistent with the general decline in the number of funds of funds, which is attributable to their fees, competition from multi-strategy funds, and their general inability to avoid losses during the recent financial crisis. Relative Value, Equity Hedge, and Event-Driven categories each encompass about 27% of the total hedge fund assets under management. The rest (about 19%) is invested with Global Macro funds. This situation changed dramatically from 1990Q4 when 40% was invested with Global Macro funds, and Event-Driven comprised only 10% of total hedge fund assets. About half (47%) of all hedge funds never reach their fifth anniversary. However, 40% of funds survive for 7 years or longer.

It is now apparent that hedge funds are not simply a fad that will disappear. The industry has matured considerably over the past two decades and now serves critical functions in the global financial system such as liquidity provision, risk transfer, price discovery, credit, and insurance. For all these reasons, a critical survey of the hedge-fund literature seems worthwhile and is undertaken in this article. In addition to providing a review of recent academic studies on hedge funds, we report updated empirical results on their performance and risk characteristics. Given how quickly the industry changes, hedge-fund data from 10 years ago may no longer be representative of today's reality, especially in the aftermath of the Financial Crisis of 2007–2009.

In preparing our review, we considered four distinct perspectives on the hedge-fund industry. The investor's perspective is most concerned with the risk/reward profile that hedge-fund strategies offer and how they compare to more traditional investment vehicles. The manager's perspective is focused on generating profitable trading strategies while managing the risks of the investments as well as the business. The regulator's perspective involves the degree to which hedge-fund blowups may spill over to the rest of the financial system and harm the real economy. And the academic's perspective consists of the many implications of hedge-fund profitability for the Efficient Markets Hypothesis, passive investing, linear factor models, and the traditional quantitative investment paradigm. Rather than choosing just one of these perspectives, we hope to broaden the usefulness of this survey by attempting to cover all four to some degree.

We begin by summarizing the basic characteristics of hedge funds in Section 2, and then review the various sources of hedge-fund data—a pre-requisite for any serious study of the industry—in Section 3. We then provide an overview of basic investment performance statistics for hedge funds in Section 4. One of the most important factors driving hedge-fund performance is illiquidity, hence we focus squarely on this issue in Section 5. Of course, hedge funds exhibit many sources of risk beyond illiquidity, and in Section 6 we explore these risks and corresponding linear and nonlinear factor models to measure and manage such risks. No survey of hedge funds would be complete without some discussion of how the industry fared during and after the recent financial crisis, and we provide such a post-mortem in Section 7. Finally, in Section 8 we turn to some practical considerations for today's hedge-fund investors, and conclude in Section 9.

2 Hedge Fund Characteristics

Hedge funds generally have more complex structural and risk characteristics than mutual funds and other traditional investment vehicles. In Sections 2.1–2.4 we highlight four of the most important of these characteristics from an investor's perspective: fees, leverage, restrictions on entering and exiting a hedge fund, and the dynamic nature of assets under management.

2.1 Fees

Most hedge funds charge annual fees consisting of two components: a fixed percentage of assets under management (typically 1% to 2%) and an incentive fee that is a percentage (typically 20%) of the fund's annual net profits, which is often defined as the fund's total earnings above and beyond some minimum threshold such as the LIBOR return, and net of previous cumulative losses (often called a "high-water mark").[1] The usual justification for such a fee structure is that the fixed fee covers the basic operating expenses of the fund, and the incentive fee aligns the interests of the manager with the investor in that the manager is paid an incentive if and only if the manager has made money for the investor not only in the current year but since inception.

Of course, the same logic should apply to portfolio managers of other types of investment vehicles such as mutual funds, exchange-traded funds (ETFs), and pension funds, yet none of them earn incentive fees. The more practical answer to why hedge funds charge an incentive fee in addition to a fixed fee is "because they can". In other words, hedge funds claim to offer unique sources of investment return, i.e., alpha, and they are willing to share some of this alpha with investors for a price. That price is the fee structure that hedge funds charge. Is it justified?

Titman and Tiu (2011) argue that better-informed hedge funds have less exposure to common-factor risks, and show that funds with less factor exposures—as measured by the R^2 of a regression of their monthly returns on various factors—tend to have higher Sharpe ratios, something investors will gladly pay for. As a result, funds in the lowest R^2 quartile charge, on average, 12 basis points more in management fees and 385 basis points more in incentive fees compared to hedge funds in the highest R^2 quartile. Goetzmann, Ingersoll, and Ross (2003) conjecture that the option-like fees commanded by hedge funds exist because hedge-fund strategies have limited capacity, hence good recent performance cannot be rewarded with fees that scale linearly with assets under management. They estimate that the present value of fees and other costs could be as high as 33% of the amount invested. However, Ibbotson, Chen, and Zhu (2011) decompose their estimated pre-fee 1995–2008 average hedge fund return of 11.13% into 3.43% of fees, 3.00% of alpha, and 4.70% of beta.

Feng, Getmansky, and Kapadia (2013) develop an algorithm to empirically estimate monthly fees, fund flows, and gross asset values of individual hedge funds. They find that management fees represent a major component in the dollar amount of total hedge fund fees (62% equally-weighted and 54% value-weighted). Anson (2001) shows that incentive fees

[1] A high-water mark is a contractual provision that requires losses in any given year to be carried forward for purposes of incentive-fee computations, so that incentive fees are paid only on net profits, i.e., profits net of any previous cumulative losses.

resemble a call option at maturity, and that hedge-fund managers can increase the value of this option by increasing the volatility of their assets. Aragon and Qian (2010) examine the role of high-water mark provisions in hedge fund compensation contracts. The authors suggest that compensation contracts in hedge funds help alleviate inefficiencies created by asymmetric information.

Fees may be relevant to investors not only because of their direct impact on returns, but also because they impact manager behavior. Using the Zurich hedge-fund database, Kouwenberg and Ziemba (2007) find that hedge funds with incentive fees have significantly lower mean returns (net of fees), while downside risk is positively related to the incentive-fee level. Agarwal, Daniel, and Naik (2009) propose using the "delta" of the hedge fund manager (defined as the expected dollar increase in the manager's compensation for a 1% increase in the fund's net asset value), the hurdle rate, and the high-water mark provision to proxy for managerial incentives. The authors find that hedge funds that have larger deltas and high-water marks perform better.

Fees are especially relevant for funds of funds, as Brown, Goetzmann, and Liang (2004) conclude. They find that individual funds dominate funds of funds in terms of net-of-fee returns and Sharpe ratios, which they attribute to the double fees implicit in fund-of-funds compensation structures. This consists of the fees charged by all the constituent funds as well as a second layer of fees charged by the fund of funds, typically a 1% fixed fee and a 10% incentive fee. Table 1 provides a simple illustration of this effect for a hypothetical fund of funds charging 1% and 10% and investing an equal amount of its assets in two funds, A and B, each charging 2% and 20%. If both of the underlying hedge-fund managers generate gross returns of 20%, the net-of-fee return for the fund-of-funds investor is a reasonably attractive 11.70%, with fees comprising 41.50% of the total gross investment returns and the rest going to the investor. However, if manager A earns a gross return of 20% and manager B loses 5%, the net-of-fee return for the fund-of-funds investor is only 2.25%; in this case, the vast majority of the total gross investment return (70%) is paid to the individual managers and the fund-of-funds manager as fees. More importantly, such a double layer of fees implies certain incentives to take on higher-risk investments as well as high-Sharpe-ratio strategies that can be leveraged at the fund of funds level so as to generate incentive fees on the portfolio of hedge funds.

2.2 Leverage

Hedge funds often employ leverage in their strategies to boost returns. Leverage involves borrowing capital—usually from banks or broker/dealers—which is used to increase a fund's

Net Returns of Fund of Funds as a Function of Underlying Managers' Investment Returns

	Manager B Return													
Manager A Return	**-15%**	**-10%**	**-5%**	**0%**	**5%**	**10%**	**15%**	**20%**	**25%**	**30%**	**35%**	**40%**	**45%**	**50%**
-15%	-18.00%	-15.50%	-13.00%	-10.50%	-8.50%	-6.50%	-4.50%	-2.50%	-0.50%	1.35%	3.15%	4.95%	6.75%	8.55%
-10%	-15.50%	-13.00%	-10.50%	-8.00%	-6.00%	-4.00%	-2.00%	0.00%	1.80%	3.60%	5.40%	7.20%	9.00%	10.80%
-5%	-13.00%	-10.50%	-8.00%	-5.50%	-3.50%	-1.50%	0.45%	2.25%	4.05%	5.85%	7.65%	9.45%	11.25%	13.05%
0%	-10.50%	-8.00%	-5.50%	-3.00%	-1.00%	0.90%	2.70%	4.50%	6.30%	8.10%	9.90%	11.70%	13.50%	15.30%
5%	-8.50%	-6.00%	-3.50%	-1.00%	0.90%	2.70%	4.50%	6.30%	8.10%	9.90%	11.70%	13.50%	15.30%	17.10%
10%	-6.50%	-4.00%	-1.50%	0.90%	2.70%	4.50%	6.30%	8.10%	9.90%	11.70%	13.50%	15.30%	17.10%	18.90%
15%	-4.50%	-2.00%	0.45%	2.70%	4.50%	6.30%	8.10%	9.90%	11.70%	13.50%	15.30%	17.10%	18.90%	20.70%
20%	-2.50%	0.00%	2.25%	4.50%	6.30%	8.10%	9.90%	11.70%	13.50%	15.30%	17.10%	18.90%	20.70%	22.50%
25%	-0.50%	1.80%	4.05%	6.30%	8.10%	9.90%	11.70%	13.50%	15.30%	17.10%	18.90%	20.70%	22.50%	24.30%
30%	1.35%	3.60%	5.85%	8.10%	9.90%	11.70%	13.50%	15.30%	17.10%	18.90%	20.70%	22.50%	24.30%	26.10%
35%	3.15%	5.40%	7.65%	9.90%	11.70%	13.50%	15.30%	17.10%	18.90%	20.70%	22.50%	24.30%	26.10%	27.90%
40%	4.95%	7.20%	9.45%	11.70%	13.50%	15.30%	17.10%	18.90%	20.70%	22.50%	24.30%	26.10%	27.90%	29.70%
45%	6.75%	9.00%	11.25%	13.50%	15.30%	17.10%	18.90%	20.70%	22.50%	24.30%	26.10%	27.90%	29.70%	31.50%
50%	8.55%	10.80%	13.05%	15.30%	17.10%	18.90%	20.70%	22.50%	24.30%	26.10%	27.90%	29.70%	31.50%	33.30%

Fees as a Percentage of Net Profits of Underlying Investments

	Manager B Return													
Manager A Return	**-15%**	**-10%**	**-5%**	**0%**	**5%**	**10%**	**15%**	**20%**	**25%**	**30%**	**35%**	**40%**	**45%**	**50%**
-15%	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	200.00%	110.00%	82.00%	68.50%	60.40%	55.00%	51.14%
-10%	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	180.00%	100.00%	76.00%	64.00%	56.80%	52.00%	48.57%	46.00%
-5%	#N/A	#N/A	#N/A	#N/A	#N/A	160.00%	91.00%	70.00%	59.50%	53.20%	49.00%	46.00%	43.75%	42.00%
0%	#N/A	#N/A	#N/A	#N/A	140.00%	82.00%	64.00%	55.00%	49.60%	46.00%	43.43%	41.50%	40.00%	38.80%
5%	#N/A	#N/A	#N/A	140.00%	82.00%	64.00%	55.00%	49.60%	46.00%	43.43%	41.50%	40.00%	38.80%	37.82%
10%	#N/A	#N/A	160.00%	82.00%	64.00%	55.00%	49.60%	46.00%	43.43%	41.50%	40.00%	38.80%	37.82%	37.00%
15%	#N/A	180.00%	91.00%	64.00%	55.00%	49.60%	46.00%	43.43%	41.50%	40.00%	38.80%	37.82%	37.00%	36.31%
20%	200.00%	100.00%	70.00%	55.00%	49.60%	46.00%	43.43%	41.50%	40.00%	38.80%	37.82%	37.00%	36.31%	35.71%
25%	110.00%	76.00%	59.50%	49.60%	46.00%	43.43%	41.50%	40.00%	38.80%	37.82%	37.00%	36.31%	35.71%	35.20%
30%	82.00%	64.00%	53.20%	46.00%	43.43%	41.50%	40.00%	38.80%	37.82%	37.00%	36.31%	35.71%	35.20%	34.75%
35%	68.50%	56.80%	49.00%	43.43%	41.50%	40.00%	38.80%	37.82%	37.00%	36.31%	35.71%	35.20%	34.75%	34.35%
40%	60.40%	52.00%	46.00%	41.50%	40.00%	38.80%	37.82%	37.00%	36.31%	35.71%	35.20%	34.75%	34.35%	34.00%
45%	55.00%	48.57%	43.75%	40.00%	38.80%	37.82%	37.00%	36.31%	35.71%	35.20%	34.75%	34.35%	34.00%	33.68%
50%	51.14%	46.00%	42.00%	38.80%	37.82%	37.00%	36.31%	35.71%	35.20%	34.75%	34.35%	34.00%	33.68%	33.40%

Table 1: Net-of-fee returns for a hypothetical fund of funds charging a 1% fixed fee and a 10% incentive fee and investing an equal amount of capital in two funds, A and B, with both funds charging a 2% fixed fee and a 20% incentive fee, for various realized annual gross-of-fee returns for A and B. Net-of-fee returns are reported as a percent of assets under management (top panel). The bottom panel reports fees as a percentage of net profits of the total gross investment returns generated by A and B. No high-water mark or clawback provisions are assumed.

investment in its strategies, thereby magnifying its gains and losses.[2] In particular, leverage increases both the expected return and volatility of any strategy. Accordingly, it is most relevant for strategies that have low volatility because they can afford to be leveraged without generating unacceptable levels of risk. However, return volatility is not the only type of risk that is relevant for leveraged investments—illiquidity risk often accompanies low-volatility investments and we shall consider this in more detail in Section 5. The amount of leverage varies considerably across hedge funds and over time, from none to a large multiple of assets under management, and margin calls are quite common during financial crises, after which many hedge funds are forced to shut down because of extreme losses stemming from excessive leverage (see Section 7).

Several authors have identified key drivers in determining how hedge funds adjust their leverage over time. Ang, Gorovyy, and van Inwegen (2011) find that economy-wide factors tend to predict changes in hedge-fund leverage better than fund-specific characteristics. Decreases in funding costs and fund return volatilities, and increases in market values all forecast increases in hedge fund leverage. The authors conclude that hedge fund leverage decreased prior to the start of the financial crisis in 2007 and was at its lowest in early 2009 when the leverage of investment banks was the highest. In a related study, Cao, Chen, Liang, and Lo (2013) show that hedge funds are able to adjust their portfolios' market exposure as aggregate market liquidity conditions change. Using a large sample of equity-oriented hedge funds from 1994 through 2009, they find strong evidence of liquidity timing ability, and in out-of-sample tests they find that top liquidity-timing funds outperform bottom liquidity-timing funds by 4.0% to 5.5% annually on a risk-adjusted basis (see Section 4.3 for further discussion).

2.3 Share Restrictions

The ability to invest or withdraw money from a hedge fund is often subject to various share restrictions. For example, new investors have to undergo a subscription process before their funds are invested in a hedge fund. Also, because of capacity constraints of a given strategy, hedge fund managers might decide to close a fund to new investors. Restrictions are also often imposed on fund withdrawals. For example, new investors (and new deposits) are often subject to a one-year "lockup" period during which investors cannot withdraw their funds. In addition, all withdrawals are subject to advance notice (typically 30 days but sometimes

[2] Leverage is typically measured by the ratio of the total gross investments, both long and short, to the assets under management. For example, a $100 million portfolio consisting of $100 million of long positions and $100 million of short positions has a total gross investment of $200 million hence its leverage ratio is 2-to-1.

as long as one year) and redemption periods (usually quarterly or annually). During periods of financial distress, hedge-fund managers sometimes impose “gates”, temporary restrictions on how much of an investor’s capital can be redeemed within a given period of time. Such restrictions are meant to protect against “fire-sale” liquidations that can generate extreme losses for the fund’s remaining investors.

Ang and Bollen (2010) model the investor’s decision to withdraw capital as a real option and treat lockups and notice periods as exercise restrictions. They estimate that a two-year lockup with a three-month notice period for redemptions is worth approximately 1% of the investment capital of an investor with constant relative risk aversion utility and a risk aversion coefficient of 3. They also find that a manager’s discretion to impose gates during times of especially high illiquidity—as many managers did during the 12- to 18-month period following the 2008 stock market decline—can cost investors much more.

Aragon (2007) studies the relation between hedge-fund returns and lockup restrictions, and concludes that hedge funds with lockup restrictions have 4% to 7% per year higher excess returns than those of non-lockup funds. Aragon, Liang, and Park (2013) find that onshore hedge funds impose stronger share restrictions than offshore hedge funds, such as a lockup provision, but hold more liquid assets. Aragon and Qian (2010) find that high-water marks are commonly used by funds that restrict investor redemptions.

Among the hedge funds that imposed gates during the recent financial crisis, Aiken, Clifford, and Ellis (2013) observe that the use of these restrictions was more common among funds with lockup provisions. This suggests that the 4–7% in excess returns reflects illiquidity risk from both lockups as well as discretionary liquidity restrictions such as gates. Ramadorai (2012) documents that funds that are gated can be traded on secondary markets for hedge funds, often at substantial discounts, but sometimes at premiums. This means that we can measure the monetary impact of share restrictions on funds. Discounts and premiums at which these shares are traded bear an intriguing resemblance to closed-end mutual-fund discounts and premiums, and are related to measures of fund illiquidity and performance.

2.4 Fund Flows and Capital Formation

A number of studies have documented a positive empirical relationship between fund flows and recent performance, suggesting that hedge-fund investors chase positive returns and flee from negative returns (Goetzmann, Ingersoll and Ross (2003), Baquero and Verbeek (2009), and Getmansky, Liang, Schwarz, and Wermers (2015)). However, the particular relation between fund flows and investment performance is often nonlinear and depends on a combination of factors including manager alpha, investor perceptions, market conditions, fund restrictions (see Section 2.3), and other hedge-fund characteristics.

Aragon, Liang, and Park (2013) find that capital flows are less sensitive to past performance in onshore funds compared to offshore funds due to regulation on advertising for onshore hedge funds. Goetzmann, Ingersoll, and Ross (2003) conjecture that unwillingness of successful funds to accept new money may be indicative of diminishing returns in the industry as a whole as investments flow in. Aragon and Qian (2010) find that high-water marks are associated with greater sensitivity of investor flows to past performance, but less so following poor performance.

Baquero and Verbeek (2009) explore the flow-performance relationship by separating inflows and outflows using a regime-switching model. They find a weak positive response of fund inflows to past performance at quarterly horizons but a very pronounced positive response of fund outflows to past performance. However, this pattern is reversed at an annual horizon. Teo (2011) evaluates a group of liquid hedge funds and concludes that for this group, funds with high net inflows subsequently outperform funds with low net inflows by 4.79% per year after adjusting for risk. He defines liquid funds as those allowing monthly or less-than-monthly redemptions. The return impact of fund flows is stronger when funds embrace liquidity risk, when market liquidity is low, and when funding liquidity (as measured by the Treasury-Eurodollar spread, aggregate hedge-fund flows, and prime broker stock returns) is tight. Fung, Hsieh, Naik, and Ramadorai (2008) find that alpha-producing funds of funds experience far greater and steadier capital inflows than non-alpha producers.

Getmansky, Liang, Schwarz, and Wermers (2015) study the effect of share restrictions on the relation between a fund's capital inflows/outflows and its performance, and document a convex flow-performance relation in the absence of share restrictions (similar to mutual funds), but a concave relation in the presence of restrictions. Further, they find that live funds are subject to stricter restrictions than defunct funds.

Baquero and Verbeek (2014) find that the lengths of winning and losing streaks (the number of subsequent quarters a fund performs above or below a given benchmark) significantly impacts future fund flows. However, the authors conclude that such a simple heuristic is sub-optimal and that investors would have performed better by simply using recursive out-of-sample forecasts from basic linear regressions.

Agarwal, Aragon, and Shi (2014) concentrate on fund flows of funds of funds. They find that funds of funds experiencing large outflows tend to liquidate holdings in funds with relatively few redemptions (i.e., liquid funds), even when these funds perform well. The authors conjecture that the best performing hedge funds are unlikely to accept capital from funds of funds that are subject to greater liquidity mismatches because hedge funds are likely to face significant redemption requests in the case of large outflows from funds of funds.

Baquero and Verbeek (2009) do not find evidence that hedge fund flows can predict future returns, i.e., the "smart money" effect.

3 An Overview of Hedge-Fund Return Data

Hedge funds are under no obligation to report their monthly returns to any parties other than their investors and the U.S. Securities and Exchange Commission (SEC).[3] However, this data is not publicly available. Because investment strategies are currently not patentable, hedge funds protect their intellectual property—which includes their historical returns—through trade secrecy. Some of the most successful hedge funds do not provide their returns to any third party, hence we can only speculate as to their performance.

Offsetting this reluctance, however, is the need for most hedge funds to attract new capital from investors. SEC Rule 502(c) of the Securities Act of 1933 bars hedge-fund advisers from general advertising, including any form of communication published in newspapers or magazines, or broadcast over television or radio. Therefore, many hedge-fund advisers choose to self-report to commercial databases in order to market their funds and attract new clients.[4] A cottage industry of hedge-fund data vendors has grown to accommodate this need, and now many hedge funds share their return information with one or more of the companies listed in Section 3.1 that maintain databases of historical hedge fund returns. Although such data are not free, potential investors and academics can purchase access through monthly or annual subscription fees. Much of what we know about hedge funds, and most of the empirical research on this industry, depends upon such archival data.

Many researchers have pointed out that the voluntary reporting of these returns yields selection biases (e.g., survivorship and back-fill bias) that can affect statistical inference in various ways, and we consider their potential impact in Section 3.2. Although biases can arise in any dataset, they are likely to be more severe when there is greater filtering of the entries, either deliberately or through industry forces. In Section 3.3, we attempt to quantify one aspect of this filtering by exploring the dynamics of hedge-fund entries and exits each year. Any financial decision based on hedge-fund data should take these biases and dynamics

[3] On October 26, 2011, the SEC unanimously voted to adopt Rule 204(b)-1 (the "Rule") under the Investment Advisers Act of 1940, as amended (the "Advisers Act"), which implements Sections 404 and 406 of the Dodd-Frank Act. The Rule requires certain SEC registered investment advisers to make periodic informational filings on Form PF detailing certain information with respect to private funds that they manage. Under the rule, as of 2012, all SEC-registered investment advisers that have at least $150 million in regulatory "assets under management" in one or more private funds have to file Form PF. However, Form PF is currently not publicly disclosed.

[4] See Ackermann, McEnally, and Ravenscraft (1999), Aiken, Clifford, and Ellis (2013), and Agarwal, Fos, and Jiang (2014).

into account in some manner.

We conclude our survey of basic hedge-fund data by describing the properties of hedge-fund indexes in Section 3.4. Despite the use of the term "index", no hedge-fund index is currently investable to the same extent as traditional indexes such as the S&P 500. Nevertheless, as indicators of broad industry performance, these indexes serve a useful purpose, and their statistical characteristics highlight some interesting differences between alternative and traditional investments.

3.1 Data Sources

Some of the most widely used hedge fund databases include Lipper TASS, Morningstar Hedge/CISDM, Hedge Fund Research (HFR), Barclay Hedge, Albourne, Eurekahedge, eVestment Alliance, HedgeFund.net, HedgeCo.net, Mercer, Russell Mellon, U.S. Offshore Funds Directory, and Wilshire (Odyssey). The type of data provided for each hedge fund may include: its net monthly returns; assets under management; style category; reporting currency; the names of the principals, fund managers, and brokers; share restrictions; audit company information; geography and composition of investments; and other information. When comparing hedge fund databases, some key considerations are the number of funds in the database, whether a graveyard database is available, and how long ago the database was established.

It can also be useful to compare the coverage of different databases: for example, do they cover complementary portions of the hedge fund universe, or are they redundant? With access to both the Lipper TASS and Morningstar Hedge/CISDM databases, we found that many of the funds are redundant even within a single database. This duplication is due to the fact that funds often have multiple legal entities employing the same investment strategy, but in different jurisdictions to accommodate onshore vs. offshore investors. For both the Lipper TASS and Morningstar Hedge/CISDM databases, roughly one-third of the funds within each of the databases are redundant. We identified redundant funds by searching for similarly-named funds with highly correlated returns. We then checked how many incremental unique funds are present in Morningstar Hedge/CISDM relative to Lipper TASS and found that roughly half the funds in the Morningstar Hedge/CISDM database are also present in the Lipper TASS database.

Schneeweis, Kazemi, and Szado (2011) compare the Lipper TASS and Morningstar Hedge/CISDM hedge fund databases further and find some differences in return and risk between the two databases at the portfolio and average manager levels. However, these differences are often relatively small. Liang (2000) compares hedge funds in the Lipper TASS and HFR databases. He finds that for identical funds tracked by both databases, returns, assets, fees, and investment style classifications can differ. He suggests that the Lipper TASS database should be used for academic research because of its relative completeness and accuracy. Much academic research does rely on the Lipper TASS database; however, a combination of databases is also used by Ackermann, McEnally, and Ravenscraft (1999), Fung and Hsieh (1997), Agarwal, Daniel, and Naik (2011), and others.

For this survey we use monthly returns data from the Lipper TASS database, subject to minor cleaning to reduce the incidence of bad data, described in Appendix A.2.

3.2 Biases

When a hedge-fund manager reports its returns to any database, this is a purely voluntary decision—managers are not required to disclose its returns to any data provider or regulator, and are free to stop reporting at any time. Therefore, a number of biases may arise among hedge-fund returns databases that are not present in other asset-pricing databases in which all securities of a given type are included, e.g., the University of Chicago's Center for Research in Security Prices (CRSP) stock returns database.

First, given that the primary motivation for participating in a database is for marketing purposes, funds generally seem to begin contributing their returns to a database after a period of outperformance. Because such funds are allowed to include prior returns upon their entry into the database, this practice leads to "backfill bias" or "instant history bias", further boosting the average returns of funds in the database which are already inflated from the selection bias associated with the decision to be listed. Fung and Hsieh (2000) estimate a backfill bias of 1.4% per year for the Lipper TASS database from 1994 through 1998. Using the Managed Account Reports database (subsequently subsumed by Morningstar Hedge/CISDM) from January 1990 to August 1998, Edwards and Caglayan (2001) estimate backfill bias of 1.2% per year.

Second, funds can choose to delist from the database at any time, and typically do so for one of two reasons: (1) fund managers decide to close their funds to new investments because they no longer have sufficient capacity; or (2) they shut down because of poor performance. These two motivations impart considerably different biases on the data—collectively known as "extinction bias"—the latter being more common and yielding a spurious favorable bias on average investment returns.

Third, some databases do not include extinct funds. This introduces "survivorship bias" and generally increases the average fund's return since the vast majority of funds that leave the database do so because they have underperformed and are shutting down.[5] Survivorship bias affects the estimated mean and volatility of hedge-fund returns as many authors have pointed out.[6] The estimated magnitude of this bias ranges from 0.16% (Ackermann, McEnally, and Ravenscraft (1999)) to 2% (Liang (2000), Amin and Kat (2003)) to 3% (Brown, Goetzmann, and Ibbotson (1999)) for offshore hedge funds).

Aggarwal and Jorion (2010b) introduce the notion of "hidden survivorship bias", which they attribute to a merger between the Lipper TASS and Tremont databases: 60% of the funds added to the Lipper TASS database between April 1999 and November 2001 are likely to be survivors, i.e., funds that were alive as of March 31, 1999. This hidden survivorship bias boosts average returns by more than 5% a year. The authors propose a sorting algorithm to exclude these funds' histories. Aggarwal and Jorion (2009 and 2010a) also find that both the performance and risk of emerging hedge funds and managers are biased. Emerging funds and managers have particularly strong financial incentives to create positive investment performance and to take on greater risk. Liang (2003) finds that data quality is directly related to auditing effectiveness—funds with more reputable auditors and more updated auditing reveal less data inconsistency.

Aggarwal and Jorion (2009) document that typical hedge-fund volatilities tend to be higher in the early years of the funds, but this result is entirely driven by the sample of dead funds. Aggarwal and Jorion (2010a) find strong evidence of outperformance during the first two to three years of existence. Joenväärä, Kosowski, and Tolonen (2014) show that variations in database coverage with respect to defunct funds, small funds, fund characteristics, assets under management, and backfill bias can lead to different performance results. The authors recommend using an aggregate database to conduct fund performance analysis, adjusting for the attrition rate and "filling in" missing observations of assets under management rather than dropping such observations from the analysis.

Fourth, most funds report their investment results net of management fees which consist of fixed and incentive fees (see Section 2.1). While the fixed fee affects the first moment of the distribution of returns, the variable incentive fee can affect higher moments and

[5]However, survivorship bias is mitigated to some degree by the fact that some of the largest and most successful funds are also not included because they have no need to raise additional assets and prefer to keep their performance strictly confidential. Nevertheless, because there are considerably more underperforming funds than outperforming ones, the net effect of survivorship bias is to impart an upward bias on average returns.

[6]See, for example, Brown, Goetzmann, Ibbotson, and Ross (1992), Schneeweis, Spurgin, and McCarthy (1996), Fung and Hsieh (1997, 2000), Hendricks, Patel, and Zeckhauser (1997), Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Carpenter and Lynch (1999), Brown, Goetzmann, and Park (2001), Liang (2001), Baquero, Horst, and Verbeek (2005), Malkiel and Saha (2005), and Horst and Verbeek (2007).

induce nonlinearities and discontinuities in standard risk/reward relations such as linear factor models (see Section 6.2). Furthermore, it is hard to reverse-engineer the gross returns with precision because incentive fees may be different for each individual investor and subject to additional considerations such as hurdle rates, high-water marks, and clawbacks. The impact of these fees makes it harder to gauge the profitability of hedge funds' strategies.

Fifth, many funds, especially larger and well-known funds that do not need any additional advertisement, are more likely to refrain from reporting to commercial databases. This "missing return bias" was first noted in Ackermann, McEnally, and Ravenscraft (1999). Edelman, Fung, and Hsieh (2013) try to capture this bias by comparing non-reporting mega hedge funds to large funds in the database. They collected information on mega funds from two industry surveys, Hedge Fund 100 and the Billion Dollar Club, and find that both sets of funds have similar behavior. However, some return differences emerge during large moves in the credit market: mega funds apparently load up on the credit factor more than other funds. The authors' overall conclusion is that an index of reporting large firms is a reasonable proxy for the performance of non-reporting mega firms.

Patton, Ramadorai, and Streatfield (2013) find that hedge fund returns change substantially depending on the vintage of the data that is provided by commonly available databases. The authors explore numerous reasons for this empirical fact and document systematic variation that suggests this is a product of the voluntary disclosure regime for hedge fund data.

Finally, Aragon and Nanda (2015) find that monthly returns are sometimes strategically delayed in reporting to the Lipper TASS database. Specifically, they observe delays of three weeks on average, but document longer delays when performance is worse, public market news is better, and fund investors are restricted from redeeming their shares. Returns also tend to be reported simultaneously in clusters. Strategic listing decisions and issues related to misreporting to hedge fund databases have been further studied by Jorion and Schwarz (2014a, 2014b), who find that hedge fund managers strategically list their small, best performing funds in multiple databases immediately while delaying listing for other funds.

In the remainder of this survey, we adjust all results for survivorship and backfill biases using the follow process. We address survivorship bias by including the Lipper TASS Graveyard database in our analysis, and we address backfill bias by deleting any returns that appear to have been backfilled. We identify and delete backfilled returns based primarily on a list of fund-inclusion dates provided by Lipper TASS. We also have access to a number of monthly database snapshots from previous years and, based on the date of a fund's first appearance in these snapshots, we are able to delete some additional backfilled returns.

Table 2 presents annualized mean, annualized volatility, skewness, kurtosis, maximum

From 1996 to 2014	# fund-months	Annualized Mean	Annualized Volatility	Skewness	Kurtosis	Maximum DD	ac(1)	Box-Q(3) p-value
Naive Estimate	351364	12.6%	5.9%	-0.25	4.41	-14.9%	0.28	0.00003
Remove Survivorship Bias	927690	9.7%	5.6%	-0.22	4.96	-15.0%	0.26	0.00009
Remove Backfill Bias	195816	11.5%	8.1%	-0.54	9.02	-19.9%	0.32	0.00000
Remove Both Biases	505844	6.3%	6.3%	-0.50	5.72	-20.5%	0.25	0.00056

Table 2: Summary statistics for cross-sectionally averaged returns from the Lipper TASS database with no bias adjustments, adjustments for survivorship bias, adjustments for backfill bias, and adjustments for both biases during the sample period from January 1996 through December 2014. For each database sample the number of fund-months, annualized mean, annualized volatility, skewness, kurtosis, maximum drawdown, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags are reported.

drawdown, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags for the Lipper TASS database without any bias adjustments and with adjustments for survivorship bias, for backfill bias, and for both during the sample period from January 1996 through December 2014. For this illustrative analysis, we constructed a time series of cross-sectionally averaged hedge fund returns. While not an investable hedge-fund proxy, this average clearly shows the general impact of these biases, which is relevant for both hedge-fund research and practical hedge-fund investment decisions. These biases make hedge funds look misleadingly attractive with respect to their average return, volatility, skewness, kurtosis, and maximum drawdown. For example, the annualized mean return across all funds using the unadjusted data is 12.6%, which is halved to 6.3% when survivorship and backfill biases are addressed. Skewness, kurtosis, and maximum drawdowns increase significantly after both bias adjustments. Volatility increases slightly, and the first-order autocorrelation stays almost the same.

3.3 Entries and Exits

The hedge-fund industry saw a prolonged boom that lasted through 2007 (see Table 3). From January 1996 through December 2006 more than twice as many new funds entered than exited the Lipper TASS database each year, despite the funds' high single-digit attrition rates. During the most recent five years, however, the process has reversed, and the number of exits has greatly exceeded the number of entries. The recent history is particularly interesting, as the number of funds peaked in 2007–2008, coinciding with the peak of the recent financial crisis. In 2008, however, the attrition rate jumped to 21%, the average return was the lowest of any year (−18.4%), and 71% of all hedge funds experience negative performance. In the years following the crisis, rather than rebounding to pre-crisis levels, the number of hedge funds reporting to the TASS database has declined markedly, particularly in the last part of the sample: 2012, 2013, and 2014. In 2014, for example, the attrition rate rose to an unprecedented 26%. This suggests that either the number of hedge funds is declining or that fewer hedge funds are choosing to report their returns to the TASS commercial database.

These industry-wide statistics obscure interesting variations within the highly heterogeneous hedge-fund industry. For example, emerging-market funds saw a spike in fund exits associated with the Asian and Russian crises: 10 exits in 1997 and 11 in 1999, but 30 exits in 1998. Fixed-income arbitrage funds, presumably investing in a manner similar to Long-Term Capital Management (LTCM),[7] saw a similar pattern: 4 exits in 1997 and 6 exits in 1999, but 13 exits in 1998.

One final striking feature of the Lipper TASS database involves funds of funds: these investment vehicles proliferated rapidly through 2007, with the number of funds growing by more than 20% every year. By the end of 2007, there were 4,506 of them in the database, and during this period (1996–2007) the attrition rate averaged 5%, lower than that of single-manager funds. However, the fund formation rate in 2008–2014 was on average only 8% per year, and the attrition rate leapt to 19% per year, implying significant decline in this sector.[8]

The survival rates of hedge funds have been estimated by a number of authors. Brown, Goetzmann, and Park (2001) show that the probability of liquidation increases with increasing risk, and that funds with negative returns for two consecutive years have a higher risk of shutting down. Liang (2000) finds that the annual hedge-fund attrition rate is 8.3% for the 1994–1998 sample period using Lipper TASS data, and Horst and Verbeek (2007) find a slightly higher rate of 8.6% for the 1994–2000 sample period. Horst and Verbeek (2007) also find that surviving funds outperform non-surviving funds by approximately 2.1% per year, which is similar to the findings of Fung and Hsieh (2000, 2002) and Liang (2000), and that investment style, size, and past performance are significant factors in explaining survival rates. Many of these patterns are also documented by Liang (2000). In analyzing the life cycle of hedge funds, Getmansky (2012) finds that the liquidation probabilities of individual hedge funds depend on fund-specific characteristics such as past returns, asset flows, age, and assets under management as well as category-specific variables such as competition and favorable positioning within the industry. Further, Liang and Park (2010) demonstrate that

[7]Note: LTCM is *not* in the Lipper TASS database.

[8]Results for formation and attrition rates for funds of funds are not reported but are available from the authors upon request.

	# Funds at Start	# Newly Reporting	# Stopped Reporting	# Funds at End	Attrition Rate	Average Return	% Neg Perf
1996	1117	354	107	1364	10%	13.5%	15%
1997	1364	371	83	1652	6%	14.0%	17%
1998	1652	368	137	1883	8%	-2.6%	42%
1999	1883	453	157	2179	8%	25.4%	16%
2000	2179	479	186	2472	9%	1.4%	38%
2001	2472	616	212	2876	9%	2.4%	32%
2002	2876	676	246	3306	9%	0.6%	45%
2003	3306	862	246	3922	7%	17.2%	10%
2004	3922	1042	311	4653	8%	7.4%	18%
2005	4653	1109	433	5329	9%	8.6%	17%
2006	5329	1135	522	5942	10%	11.3%	13%
2007	5942	1217	865	6294	15%	8.7%	19%
2008	6294	997	1347	5944	21%	-18.4%	71%
2009	5944	953	855	6042	14%	16.6%	21%
2010	6042	848	878	6012	15%	9.1%	17%
2011	6012	657	971	5698	16%	-3.7%	55%
2012	5698	487	1058	5127	19%	6.0%	23%
2013	5127	288	1057	4358	21%	7.0%	21%
2014	4358	129	1128	3359	26%	3.2%	29%

Table 3: Statistics for entries and exits of single-manager hedge funds, including number of entries, exits, and funds at the start and end of a given year, attrition rate, average return, and percentage of funds that performed negatively are reported for each year from January 1996 through December 2014. Source: Lipper TASS database.

traditional risk measures like standard deviation cannot easily predict fund attrition, while downside risk measures, including fat tails, are more effective.

Brown, Goetzmann, and Park (2001) find that the half-life of typical Lipper TASS hedge funds is 30 months, while Brooks and Kat (2002) estimate that approximately 30% of new hedge funds do not make it past 36 months due to poor performance and Amin and Kat (2003) find that 40% of their sample of hedge funds do not make it to the fifth year. Howell (2001) observes that the probability of hedge funds failing in their first year is 7.4%, only to increase to 20.3% in their second year. Poor-performing younger funds drop out of databases at a faster rate than older funds (see Getmansky (2012) and Jen, Heasman, and Boyatt (2001)), presumably because younger funds are more likely to take additional risks to obtain good performance which they can use to attract new investors, whereas older funds that have survived already have track records with which to attract and retain capital.

Ineichen (2001), Kramer (2001), Feffer and Kundro (2003), and Getmansky, Lo, and Mei (2004) study the reasons for hedge-fund liquidations, and categorize funds as "liquidated" due to failure or fraud, or because they are no longer reporting to the database, closed to new investment, or have merged into another entity. Ineichen (2001) describes and expands on an explanation for hedge-fund disasters first advanced in 2000 by Louis Bacon—founder of the successful hedge fund Moore Capital Management—who proposes five early warning signs: excess size, excess leverage, lack of transparency, funding mismatches, and hubris. Kramer (2001) focuses on fraud, providing detailed accounts of six of history's most egregious cases. Feffer and Kundro (2003) conclude that "half of all failures could be attributed to operational risk alone", of which fraud is one example. Getmansky, Lo, and Mei (2004) document the empirical properties of a sample of 1,765 funds in the TASS Hedge Fund database from 1977 to 2004 that are no longer active. They find that attrition rates differ significantly across investment styles—from a low of 5.2% per year on average for convertible arbitrage funds to a high of 14.4% for managed futures funds—and relate a number of factors to these attrition rates, including past performance, volatility, and investment style. They also find differences in illiquidity risk between active and liquidated funds, with active funds exhibiting smoother returns which are associated with more illiquid investments. They attribute this difference to three potential explanations: smoother returns are indicative of better risk control, which leads to lower attrition rates; smoother returns have higher Sharpe ratios which are more attractive to investors; and the illiquidity premium increases expected returns, making these investments more attractive than more liquid counterparts.

Aragon and Qian (2010) find that funds with high-water marks in their fee structures can reduce inefficient liquidation by raising after-fee returns following poor performance. Studying funds of funds, Fung, Hsieh, Naik, and Ramadorai (2008) find that alpha-producing funds are not as likely to liquidate as those that do not deliver alpha.

Finally, Liang and Park (2010) find that funds with larger downside risk have a higher hazard rate, after controlling for style, performance, fund age, size, lockup, high-water mark, and leverage. The authors show that the real failure rate of hedge funds is 3.1% compared to the attrition rate of 8.7% on an annual basis using 1995–2004 data. This implies that hedge fund liquidation does not necessarily mean failure in the hedge-fund industry.

3.4 Hedge Fund Indexes

Just as investors find it useful to have a data vendor calculate and disseminate equity indexes such as the S&P 500, the Dow Jones Industrial Average, the Russell 2000, and the MSCI World, hedge-fund investors find it useful to be able to see a measure of the average performance of the hedge-fund industry. Accordingly, several firms calculate and disseminate such aggregates. Because the industry is so heterogeneous, these firms generally also publish category indexes. While some of these indexes are well over a decade old, a more recent phenomenon is the emergence of daily hedge-fund indexes. Typically based on the returns of a smaller number of hedge funds (relatively few hedge funds are willing to share daily performance data), these indexes are less common.

Before turning to the properties of some commonly cited hedge-fund indexes in Section 4, it is important to qualify these results with the observation that such indexes are not investable in the same way that popular equity and fixed-income indexes are investable. This qualification is significant because many institutional investors such as pension funds base their investment decisions on the properties of indexes. They have come to depend on indexes because, as mostly passive investors, they concentrate on keeping costs to a minimum and earning expected returns through buy-and-hold investments in assets that offer reasonable long-term risk premia from "beta" or common risk exposures. Accordingly, such investors focus more on asset-allocation decisions across asset classes, e.g., equities, fixed income, and commodities, and within each asset class, the majority of the returns are generated through low-cost passive vehicles that track the corresponding "benchmarks" to within basis points of their monthly returns. Such benchmarks are almost always indexes such as the S&P 500 which have liquid investment vehicles like pooled funds and separately-managed accounts that invest directly in the underlying securities, futures and swap contracts on such indexes, ETFs, and more customized over-the-counter derivatives contracts. The combined effect of these offerings is to allow large institutional investors to realize the stated performance of indexes even when investing billions of dollars at a time.

The same cannot be said for any existing hedge-fund index. While some indexes include funds still open to new investors, it is not yet possible to invest a billion dollars of assets within a 30-day period in a hedge-fund index and expect to achieve nearly the same return realized by that index during the same period. In contrast, the investment returns of a \$1 billion investment in the S&P 500 can be achieved by purchasing 3,042 S&P 500 futures contracts on the Chicago Mercantile Exchange.[9] This kind of passive, liquid, and near-perfect index tracking is not yet possible for any existing hedge-fund index, hence hedge-fund index performance results should be interpreted with this caveat in mind.

A List of Hedge Fund Indexes

Index Type	Index Provider	Includes Total Industry Index	Includes Category Indexes
Monthly	Credit Suisse/Dow Jones	Yes	Yes
	Hedge Fund Research	Yes	Yes
	Eurekahedge	Yes	Yes
	Hennessee	Yes	Yes
	Barclay Hedge	Yes	Yes
	MSCI	Yes	Yes
	Morningstar	Yes	Yes
	CISDM	Yes	Yes
Daily	Hedge Fund Research	Yes	Yes
	Credit Suisse/Dow Jones	Yes	Yes
	Barclay Hedge	No	CTAs Only
Replication	Credit Suisse/Dow Jones	Yes	Yes

Table 4: Information about hedge-fund index providers, index family, and the availability of total-industry and category indexes for commonly used monthly, daily, and replication hedge-fund indexes.

Billio, Getmansky, and Pelizzon (2009) examine four daily hedge-fund return indexes (MSCI, FTSE, Dow Jones, and HFRX), all based on investable hedge funds, and three monthly hedge fund return indexes (CSFB Tremont, CISDM, and HFR), which comprise both investable and non-investable hedge funds. They find that key variables like fund selection, asset liquidity, data frequency, sample period, and index-construction method have significant explanatory power for a number of statistical properties of hedge-fund indexes. One of the most important of these key variables is "investability".

[9] As of Wednesday May 23, 2012, the S&P 500 futures price for the June 2012 contract was 1315.70, and the contract specification was 250 times the futures price, yielding a notional value of \$328,952 per contract, hence 3,042 contracts would generate a notional exposure of \$1,000,589,850.00. On that day, the estimated total volume of such contracts traded was 13,438 and the prior day's open interest was 259,289, so 3,042 contracts would be a significant but not an infeasible position to establish over the course of a few trading days.

A new group of indexes is built around the idea of "factor replication". These indexes generally aim to answer the following question: if a portfolio of liquid instruments is formed to match the performance of the investable liquid-beta portion of typical hedge funds' portfolios, what would its returns be? These indexes can be used in determining whether funds of funds are delivering alpha or beta, or as the basis for hedge-fund beta replication products (see Section 6.6). This group consists of two subgroups: daily replication indexes published by data vendors who seem to have begun calculating them as an extension of their existing index business, and indexes published by asset management firms whose motivation appears to be the support of hedge-fund beta replication funds launched by the same firms. We include only the former subgroup in our summary.

In Table 4 we report information about index providers, index families, and the availability of the total industry and category indexes for commonly used hedge-fund indexes. Monthly indexes reflect the returns of hedge funds that report to databases at a monthly frequency. Daily indexes reflect the returns of hedge funds that are willing to report their returns daily. Replication indexes are daily indexes that show the hypothetical profit and loss for a factor-model-based hedge-fund beta replication strategy. The Total Industry Index represents the aggregate performance of the entire hedge-fund industry. A Category Index is designed to represent the performance of funds within a specific category.

4 Investment Performance

Despite the heterogeneity and uniqueness of individual hedge funds, most hedge funds share common characteristics with others that deploy similar strategies and/or invest in similar financial markets and securities. Based on these commonalities, hedge funds may be clustered into "styles" or "categories". One popular categorization is that provided by the Lipper TASS database, which contains 11 main groupings: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity Hedge, Managed Futures, Multi-Strategy, and Fund of Funds (see the Appendix for definitions of these categories). While these categories do provide a useful nomenclature for interpreting the investment performance of hedge funds, it should be emphasized that the heterogeneity within any single category is considerably greater than that of traditional investment categories such as large-cap growth or small-cap value funds. We will illustrate both the commonalities and the heterogeneity of hedge-fund styles through the statistical properties of their investment returns.

We begin in Section 4.1 with a summary of the hedge-fund performance literature in which the risks and rewards of hedge funds are linked to attributes such as managerial incentive structures, managers' ability to hedge, strategy distinctiveness, connections with political lobbyists, education and career concerns, confidential holdings, delayed reporting, managerial skills, and capacity constraints. While several of these links are intuitive, the more important questions are whether or not they imply performance persistence (which we consider in Section 4.2), and whether hedge-fund managers can actively change their positions and leverage in response to changes in market conditions (which we consider in Section 4.3)? In Section 4.4 we show that hedge funds are not all alike by comparing the investment performance of funds across different style categories, and we also show that hedge funds are not all unique by identifying a number of common factors among them that may reduce their diversification properties. We explore the investment implications of these empirical findings in Section 8.3.

4.1 Basic Performance Studies

The empirical properties of hedge-fund performance have been documented by many authors using several of the databases cited in Section 3.[10] Unlike the literature on mutual-fund performance, a number of these studies document positive risk-adjusted returns in the hedge-fund industry, i.e., positive alphas.[11] In fact, using data from 1995 to 2009, Ibbotson, Chen, and Zhu (2011) find that alphas were positive every year of the past decade, even during the recent financial crisis. More specifically, using a sample of 4,750 stock swap mergers, cash mergers, and cash tender offers from 1963 to 1998, Mitchell and Pulvino (2001) find that risk-arbitrage strategies generated excess returns of 4% per year.

Fung, Hsieh, Naik, and Ramadorai (2008) investigate performance, risk, and capital formation in the hedge-fund industry from 1995 to 2004, and over their 120-month sample, they find that the average fund of funds delivered positive and statistically significant alpha only in the 18-month sub-period between October 1998 and March 2000. Malkiel and Saha (2005) report that, after adjusting for various hedge-fund database biases, hedge funds significantly underperform their benchmarks on average, and our results confirm these findings. In a sample of 7,000 hedge funds, Billio, Frattarolo, and Pelizzon (2014) find that alpha changes

[10]See, for example, Ackermann, McEnally, and Ravenscraft (1999), Liang (1999, 2001, 2003), Agarwal and Naik (2000b, 2000c), Fung and Hsieh (2000, 2001), Edwards and Caglayan (2001), Kao (2002), and Kosowski, Naik, and Teo (2007). More detailed performance attribution and style analysis for hedge funds has been considered by Fung and Hsieh (1997, 2002), Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2000b, 2000c), Brown, Goetzmann, and Park (2000, 2001), Liang (2001),Lochoff (2002), and Brown and Goetzmann (2003).

[11]See Brown, Goetzmann, and Ibbotson (1999), Ackermann, McEnally, and Ravenscraft (1999), Liang (1999), Agarwal and Naik (2000a,b,c), Fung and Hsieh (2004), Kosowski, Naik, and Teo (2007), and Fung, Hsieh, Naik, and Ramadorai (2008).

dramatically through time, across categories, and is related to the level of competition among hedge funds.

Several studies link hedge-fund performance to various hedge-fund and strategy characteristics such as managerial incentive structures, geography, career concerns, strategy capacity, strategy distinctiveness, political connections, and even manager SAT scores. Agarwal, Daniel, and Naik (2009) find that hedge funds with greater managerial incentives (proxied by the delta of option-like incentive fee contracts), higher levels of managerial ownership, and the inclusion of high-water mark provisions in the incentive contracts are associated with superior performance. Getmansky (2012) documents a concave relationship between size and performance for illiquid and capacity-constrained hedge funds, which connects strategy capacity with fund performance. Ramadorai (2013) defines capacity constraints based on past flows, fund size, and a novel variable—an indicator variable that indicates whether the fund's management company launched a new fund or a new share class. Consistent with other results in the literature, he finds that capacity constraints lead to a reduction in future returns.

Sun, Wang, and Zheng (2012) show that hedge-fund strategy distinctiveness is associated with higher performance, and Titman and Tiu (2011) find that managers' ability to hedge is directly related to hedge-fund performance. Gao and Huang (2014) conclude that hedge-fund managers gain an informational advantage in securities trading through their connections with political lobbyists. They identify politically sensitive companies as those with high lobbying expenditures relative to their operating cash flows and find that politically connected hedge funds outperform non-connected funds by 1.6% to 2.5% per month on their holdings of politically sensitive stocks as compared to their less politically sensitive holdings. Teo (2009) shows that hedge funds with headquarters or a research office in their investment region outperform those without it, suggesting that local funds possess an informational advantage. Liang and Park (2007) show that downside risk measures incorporating higher return moments can effectively predict future fund performance. And Li, Zhang, and Zhao (2011) conclude that education and career concerns can positively impact hedge fund performance—managers from undergraduate institutions with higher average SAT scores apparently have higher raw and risk-adjusted returns.

Hedge-fund performance has also been linked to macroeconomic factors. For example, Avramov, Kosowski, Naik, and Teo (2011) show that conditioning on macroeconomic variables such as the Chicago Board Options Exchange Volatility Index (VIX) and default spreads is important in detecting managerial skill, and this information can be exploited in forming optimal portfolios of hedge funds. These results can be interpreted in at least two ways: managerial alpha is, in fact, attributable to "exotic betas", or hedge-fund managers generate alpha when macro conditions are conducive. We shall have more to say about factors driving hedge-fund returns in Section 6.

An important focus of research on hedge fund performance is managers' ability to perform during periods of market distress. Gao, Gao, and Song (2014) show that hedge-fund managers with better skills in exploiting the market's ex ante disaster concerns deliver superior returns. Jiang and Kelly (2012) find that hedge funds are exposed to downside "tail risk" (the risk of rare events), so that a one-standard deviation positive shock to tail risk is associated with a contemporaneous decline of 2.88% per year in the value of the aggregate hedge-fund portfolio.

There is also a growing literature on the long-equity holdings of hedge funds retrieved from 13F filings with the SEC.[12] Brunnermeier and Nagel (2004) examine long stock holdings of hedge funds during the time of the Technology Bubble in 2000 and find that hedge funds reduced their exposure to technology stocks before prices collapsed and their technology stock holdings outperformed characteristics-matched benchmarks. Griffin and Xu (2009) show that hedge-fund managers are only marginally better than mutual-fund managers in stock picking, and also find weak evidence of differential ability among hedge funds.

Agarwal, Jiang, Tang, and Yang (2013) study quarter-end equity holdings of hedge funds that are disclosed with a delay through amendments to their 13F filings. Hedge-fund managers delay reporting their positions due to concerns about private information and price impact. Hedge funds managing large and concentrated portfolios, adopting non-standard investment strategies with higher idiosyncratic risk, and holding stocks associated with information-sensitive events such as mergers and acquisitions seek confidentiality more frequently. The authors find that confidential holdings exhibit superior performance up to twelve months, and take longer to build. Aragon, Hertzel, and Shi (2013) find that managers seek confidential treatment of some of their 13F-reportable positions in order to hide confidential information from the public. The hedge fund managers are also more likely to seek confidential treatment of illiquid positions that are more susceptible to front-running. 13F public filings thus are likely to attract informed hedge fund traders and investors. However, there are some significant challenges in the detection of informed trading by hedge funds because they pertain to a narrow scope of reportable securities, exclude short positions, and are observable at a low (quarterly) frequency.

[12]Standard databases such as Thomson-Reuters Institutional Holdings systematically omit certain positions that are 13F-reportable such as call- and put-option positions (Aragon and Martin (2012)), and confidentially held stock positions (Agarwal, Jiang, Tang, and Yang (2013), Aragon, Hertzel, and Shi (2013)), hence researchers should also check SEC filings directly.

4.2 Performance Persistence

The evidence regarding performance persistence is mixed. Agarwal and Naik (2000a) and Chen (2007) find that monthly hedge-fund performance persists for short periods, but disappears at an annual horizon. Using annual offshore hedge-fund data, Brown, Goetzmann, and Ibbotson (1999) find no evidence of performance persistence. Edwards and Caglayan (2001) use both parametric and non-parametric procedures to study persistence over one- and two-year horizons and also find no persistence, though they do observe considerable variation across style categories. Boyson (2008) does not find any performance persistence over short and long intervals when funds are selected based purely on past performance, but when manager tenure is taken into consideration, hedge funds do seem to exhibit performance persistence over quarterly intervals.

However, Bares, Gibson, and Gyger (2003) do find short-term persistence, and Baquero, Horst, and Verbeek (2005) find persistence in hedge funds at the quarterly frequency after correcting for investment styles, but persistence is statistically insignificant annually. Kat and Menexe (2003) find weak persistence in mean returns, but strong persistence in hedge funds' standard deviations and their correlation with the stock market. Fung, Hsieh, Naik, and Ramadorai (2008) find that there is a greater chance for a fund to deliver alpha in the subsequent two-year period if it has positive estimated alpha in the previous two-year period. In particular, they show that the overall average transition probability for a positive-alpha fund into the subsequent positive-alpha group is 28%, while the transition probability for a no-alpha fund is only 14%. Moreover, the year-by-year alpha-transition probability for a positive-alpha fund is always higher than that for a no-alpha fund, implying greater alpha persistence among members of the positive-alpha group. Consistent with these findings, Jagannathan, Malakhov, and Novikov (2010) document significant performance persistence among superior hedge funds, while they find little evidence of persistence among inferior funds.

Persistence in hedge fund performance challenges the no-persistence equilibrium result of the Berk and Green (2004) model for mutual funds. Extending the model to deliver persistence in a hedge fund setting may be an interesting direction for future research (e.g., Glode and Green (2011)).

4.3 Timing Ability

Among the entire population of professional investment managers, hedge funds should be the most likely to display timing skills of some form given that they are less constrained and more active. In fact, because of their broader investment mandates and greater flexibility to exploit investment opportunities as they emerge, hedge funds can engage in several forms of timing, e.g., market timing, volatility timing, and liquidity timing. The empirical evidence generally seems to support this intuition.

Fung, Xu, and Yau (2002) examine global hedge-fund managers and conclude that they do not show positive market timing ability, but have superior security-selection ability. Aragon (2005) finds that funds of funds do not exhibit timing ability, but that market-timing ability is positive for funds holding the most liquid portfolios and negative for funds holding the most illiquid portfolios. However, Chen (2007) extends the timing measures in Treynor and Mazuy (1966) and Henriksson and Merton (1981) and finds significant market-timing ability for individual hedge funds and funds of funds in bond, currency, and equity markets. Chen and Liang (2007) propose a new market-timing measure by relating fund returns to the squared Sharpe ratio of the market portfolio. Using a sample of 221 market-timing funds from January 1994 through June 2005, they find economically and statistically significant evidence of return timing, volatility timing, and joint timing, both at the aggregate and individual-fund levels.

Kazemi and Li (2009) consider the market- and volatility-timing ability of commodity trading advisors (CTAs), and observe that CTAs display a negative relationship between market-timing and security-selection ability. They also find that systematic CTAs are, in general, better at market timing than discretionary CTAs. Cave, Hubner, and Sougne (2012) identify "positive", "mixed", and "negative" market timers and study their performance during the financial crisis of 2007–2009. Aragon and Martin (2012) study volatility timing ability and selectivity skill revealed by the use of calls, puts, and equity positions by hedge-fund investment advisers. They find that hedge funds successfully use derivatives to profit from private information about stock fundamentals. For example, hedge funds greatly increased their use of puts in the aftermath of the Technology Bubble, and there is a strong positive (negative) relation between call (put) holdings and subsequent abnormal stock returns. Chen (2011) finds that 71% of hedge funds trade derivatives. After controlling for fund strategies and characteristics, derivatives users on average exhibit lower market, downside, and event risk.

Cao, Chen, Liang, and Lo (2013) examine the liquidity timing ability for hedge funds, and find strong evidence at both the strategy and individual-fund levels. Specifically, they show that hedge-fund managers increase (decrease) their portfolios' market exposure when equity-market liquidity is high (low), and liquidity timing is most pronounced when market liquidity is very low.

4.4 Hedge-Fund Styles

Despite the heterogeneity among hedge funds and their myriad strategies, they do fall into several broad groupings or categories of investment "styles". Fung and Hsieh (1997) study hedge-fund styles and find that the strategies are highly dynamic and behave very differently from those used by mutual funds. To develop some intuition for these styles and how they are related, we report in Table 5 the correlations of monthly average returns of hedge funds in each Lipper TASS style category from January 1996 through December 2014. These estimates show that the correlations between some categories' average returns are as high as 0.77 (between Event Driven and Convertible Arbitrage categories), but Long/Short Equity Hedge and Dedicated Short Bias are negatively correlated at -0.74, and Managed Futures has virtually no correlation with any other category except for Global Macro. Fixed Income Arbitrage and Convertible Arbitrage have much in common, and Event Driven is highly correlated with several categories. Meanwhile, the Equity Market Neutral and Global Macro categories have, at most, moderate correlations with other styles.

Category Correlations 1996-2014	*Convertible Arbitrage*	*Dedicated Short Bias*	*Emerging Markets*	*Equity Market Neutral*	*Event Driven*	*Fixed Income Arbitrage*	*Global Macro*	*Long/Short Equity Hedge*	*Managed Futures*	*Multi-Strategy*	*Fund of Funds*	*All Single Manager Funds*
Convertible Arbitrage	1.00	-0.41	0.63	0.55	0.77	0.69	0.23	0.61	-0.08	0.66	0.63	0.69
Dedicated Short Bias	-0.41	1.00	-0.57	-0.25	-0.60	-0.17	-0.15	-0.74	0.03	-0.53	-0.55	-0.66
Emerging Markets	0.63	-0.57	1.00	0.41	0.78	0.47	0.40	0.78	0.05	0.71	0.85	0.88
Equity Market Neutral	0.55	-0.25	0.41	1.00	0.59	0.46	0.18	0.49	0.04	0.54	0.46	0.52
Event Driven	0.77	-0.60	0.78	0.59	1.00	0.58	0.32	0.80	0.01	0.75	0.81	0.86
Fixed Income Arbitrage	0.69	-0.17	0.47	0.46	0.58	1.00	0.32	0.37	0.03	0.49	0.50	0.50
Global Macro	0.23	-0.15	0.40	0.18	0.32	0.32	1.00	0.33	0.55	0.43	0.54	0.51
Long/Short Equity Hedge	0.61	-0.74	0.78	0.49	0.80	0.37	0.33	1.00	0.09	0.74	0.84	0.94
Managed Futures	-0.08	0.03	0.05	0.04	0.01	0.03	0.55	0.09	1.00	0.23	0.29	0.24
Multi-Strategy	0.66	-0.53	0.71	0.54	0.75	0.49	0.43	0.74	0.23	1.00	0.83	0.83
Fund of Funds	0.63	-0.55	0.85	0.46	0.81	0.50	0.54	0.84	0.29	0.83	1.00	0.94
All Single Manager Funds	0.69	-0.66	0.88	0.52	0.86	0.50	0.51	0.94	0.24	0.83	0.94	1.00

Table 5: Monthly correlations of the average returns of funds in each hedge-fund style category. Correlations for the 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database from January 1996 through December 2014 are reported. The All Single Manager Funds category includes the funds in all 10 main Lipper TASS categories and any other single-manager funds present in the database (relatively few) while excluding funds of funds. Correlations are color-coded with the highest correlations in blue, intermediate correlations in yellow, and the lowest correlations in red.

To develop further insight into these correlations, we consider a simple factor model based on principal component analysis (PCA). From a PCA perspective, correlated hedge-fund investment styles can be decomposed into a linear combination of uncorrelated "eigen-strategies". PCA can tell us just how many uncorrelated eigen-strategies underpin the majority of the performance of the 10 hedge-fund categories listed in Table 5. We find that 79% of the strategies' volatility-equalized variances is explained by only three factors, suggesting that a large fraction of hedge funds' returns are generated by a very small universe of uncorrelated strategies. The fraction of variance explained by each of the first six eigenvalues is as follows:

$$\{\lambda_1 : 52.3\%, \lambda_2 : 15.0\%, \lambda_3 : 11.0\%, \lambda_4 : 6.3\%, \lambda_5 : 3.7\%, \lambda_6 : 3.5\%\}.$$

To put the magnitude of these eigenvalues in context, we simulated one million correlation matrices each based on 216 independently and identically distributed (IID) Gaussian returns of 10 simulated time series from which we computed an empirical distribution of the matrices' largest eigenvalues. The mean of this distribution is 13.51%, while the minimum and maximum are 11.59% and 17.18%, respectively—all much smaller than the estimated λ_1.[13] This suggests that the first principal component accounts for significantly more variability than in the case of purely random returns, and hedge-fund category returns do have factors in common.

As with any PCA decomposition, the principal components may not be easily interpretable and we caution against reading too much into their significance. However, the distribution of the corresponding eigenvalues provides some insight into how many genuinely unique investment strategies are reflected in category returns. In this respect, the PCA results are informative: the 10 categories' returns are certainly not unique, but neither are they all explained by a single factor. On the one hand, hedge-fund investors should be mindful that the returns of any two hedge-fund styles may be driven by completely uncorrelated factors and that, far from any two hedge-fund investments being interchangeable, the choice of hedge-fund style may be as significant as the choice between stocks and bonds. On the other hand, because 80% of hedge-fund category returns are implicitly driven by three factors, hedge-fund investors should also recognize that the benefits of diversification are limited; the returns of, say, 20 hedge funds are unlikely to be completely uncorrelated.

[13] For robustness we repeated the million-sample simulation using a fat-tailed distribution (the t distribution with one degree of freedom) and reached the same conclusion. The mean proportion of variance explained by the largest eigenvalue is 13.57%, while the minimum and maximum are 10.24% and 37.23%, respectively. Even with a fat-tailed distribution it is very unlikely that λ_1 could be as large as 52.3% by chance.

A more intuitive illustration of the heterogeneity and commonality among hedge-fund styles is presented in Table 6, in which a variety of summary statistics such as average return, volatility, Sharpe ratio, and higher-order moments are reported for hedge-fund category returns. The top panel reports the summary statistics for the average fund (averaged across all available funds in the Lipper TASS database for each month), and the bottom panel reports the same summary statistics for the Credit Suisse/Dow Jones (CS/DJ) Hedge-Fund Category Index.

From 1996 to 2014		# fund-months	Annualized Mean	Annualized Volatility	Sharpe Ratio	Sortino Ratio	Skewness	Kurtosis	Maximum DD	S&P 500 Correl.	ac(1)	Box-Q(3) p-value
Database Estimate	*Convertible Arbitrage*	14231	5.4%	7.3%	0.38	0.51	-3.37	28.94	-34.4%	0.51	0.48	0.00
Database Estimate	*Dedicated Short Bias*	2503	-1.1%	15.6%	-0.23	-0.41	0.62	5.23	-47.3%	-0.72	0.10	0.08
Database Estimate	*Emerging Markets*	47054	6.8%	14.2%	0.29	0.42	-1.43	9.94	-49.3%	0.64	0.31	0.00
Database Estimate	*Equity Market Neutral*	27459	4.7%	3.3%	0.61	0.99	-0.25	12.86	-14.6%	0.32	0.20	0.00
Database Estimate	*Event Driven*	39227	6.8%	5.9%	0.70	1.05	-1.64	8.97	-24.8%	0.65	0.42	0.00
Database Estimate	*Fixed Income Arbitrage*	18834	5.1%	4.4%	0.56	0.68	-4.35	32.93	-20.7%	0.29	0.37	0.00
Database Estimate	*Global Macro*	32034	4.9%	5.2%	0.44	0.81	0.48	4.93	-14.2%	0.28	0.01	0.48
Database Estimate	*Long/Short Equity Hedge*	178926	7.7%	9.0%	0.56	0.98	0.00	5.47	-24.7%	0.74	0.22	0.00
Database Estimate	*Managed Futures*	46204	4.8%	9.4%	0.23	0.44	0.26	3.13	-16.3%	-0.05	-0.02	0.29
Database Estimate	*Multi-Strategy*	76233	5.8%	5.2%	0.62	0.93	-1.18	7.16	-21.5%	0.57	0.22	0.00
Database Estimate	*Fund of Funds*	270369	3.8%	6.0%	0.20	0.31	-0.57	6.80	-21.9%	0.58	0.28	0.00
Database Estimate	*All Single Manager Funds*	505844	6.3%	6.3%	0.58	0.97	-0.50	5.72	-20.5%	0.71	0.25	0.00
CS/Dow Jones Index	*Convertible Arbitrage*	228	7.3%	6.8%	0.69	0.95	-2.75	20.03	-32.9%	0.37	0.55	0.00
CS/Dow Jones Index	*Dedicated Short Bias*	228	-6.4%	16.7%	-0.53	-0.95	0.78	4.65	-76.3%	-0.77	0.08	0.53
CS/Dow Jones Index	*Emerging Markets*	228	8.4%	13.1%	0.44	0.65	-1.28	10.74	-45.1%	0.60	0.26	0.00
CS/Dow Jones Index	*Equity Market Neutral*	228	4.8%	10.2%	0.21	0.23	-11.88	165.26	-45.1%	0.31	0.07	0.06
CS/Dow Jones Index	*Event Driven*	228	9.2%	6.3%	1.03	1.52	-2.25	13.60	-19.1%	0.63	0.36	0.00
CS/Dow Jones Index	*Fixed Income Arbitrage*	228	5.3%	5.6%	0.48	0.58	-4.64	36.20	-29.0%	0.32	0.53	0.00
CS/Dow Jones Index	*Global Macro*	228	10.9%	8.9%	0.92	1.60	-0.06	8.01	-26.8%	0.24	0.05	0.30
CS/Dow Jones Index	*Long/Short Equity Hedge*	228	9.7%	9.6%	0.72	1.29	-0.03	6.63	-22.0%	0.67	0.18	0.04
CS/Dow Jones Index	*Managed Futures*	228	6.1%	11.4%	0.30	0.57	0.06	2.69	-17.4%	-0.05	0.03	0.21
CS/Dow Jones Index	*Multi-Strategy*	228	8.4%	4.9%	1.16	1.77	-1.99	11.52	-24.7%	0.43	0.44	0.00
CS/Dow Jones Index	*All Single Manager Funds*	228	8.6%	7.1%	0.82	1.44	-0.20	6.27	-19.7%	0.59	0.17	0.01

Table 6: Summary statistics for the returns of the average fund in each Lipper TASS style category and summary statistics for the corresponding CS/DJ Hedge-Fund Index. Number of fund months, annualized mean, annualized volatility, Sharpe ratio, Sortino ratio, skewness, kurtosis, maximum drawdown, correlation coefficient with the S&P 500, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags for the 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database from January 1996 through December 2014 are reported. Sharpe and Sortino ratios are adjusted for the three-month U.S. Treasury Bill rate. The "All Single Manager Funds" category includes the funds in all 10 main Lipper TASS categories and any other single-manager funds present in the database (relatively few) while excluding funds of funds.

We observe new patterns of similarities and differences among hedge fund categories in Table 6. During the period from January 1996 through December 2014, Dedicated Short Bias underperformed all categories, which is not surprising given that equities performed well during a significant portion of the sample period. Consistent with Agarwal and Kale (2007) we find that Multi-Strategy hedge funds outperformed Funds of Funds. The average

Managed Futures fund's returns appear roughly IID and Gaussian, while the returns of the average Convertible Arbitrage fund are autocorrelated and have fat tails. Although some categories are uncorrelated or negatively correlated with stocks, Long/Short Equity Hedge, Event Driven, and Emerging Markets funds have correlations with the S&P 500 total return index of 0.74, 0.65, and 0.64, respectively. High correlation with a traditional equities-based portfolio can undermine hedge funds' diversification advantage.

Return volatility also differs considerably across categories. For example, volatility of the average Emerging Markets fund is three times greater than that of the average Fixed Income Arbitrage fund. Intriguingly, lower volatility does not unambiguously imply lower risk: Managed Futures has high volatility but low maximum drawdown, while Fixed Income Arbitrage and Multi-Strategy hedge funds have roughly half the volatility but a higher maximum drawdown. These last two categories also have a history of negative skewness and large kurtosis, i.e., their returns have fat left tails. Heuson, Hutchinson, and Kumar (2015) show that traditional performance measures systematically under-estimate (over-estimate) managerial performance when returns exhibit positive (negative) skewness, and propose a new measure to account for skewness in performance measurement.

Figure 1 suggests that categories that exhibit higher autocorrelation generally also exhibit kurtosis and negative skewness (we show in Section 5 that positive autocorrelation is a proxy for illiquidity risk). This cluster of traits should give investors cause for concern, so it is worth listing the hedge-fund styles that most clearly exhibit them: Convertible Arbitrage, Fixed Income Arbitrage, Event Driven, Emerging Markets, and Multi-Strategy. These strategies have the highest autocorrelations and the most fat-tailed return distributions. When investing in a fund with positively autocorrelated returns, investors may want to consider the increased likelihood that a simple analysis based on the returns' volatility will understate the actual downside risk.

The extremely high autocorrelation of several categories' returns demands further study, hence in Figure 2 we display the 36-month rolling-window autocorrelation for each category. Some categories exhibit consistently high autocorrelation while others exhibit little or negative autocorrelation. Curiously, some categories' autocorrelations increased sharply during the financial crisis while others' were unaffected. For example, Figure 2(a) depicts, among others, the 36-month rolling-window autocorrelation of the Convertible Arbitrage strategy from January 1996 through December 2014. A comparison with subsequent figures shows that over 19 years the average returns of funds in the Convertible Arbitrage category have generally been more autocorrelated than those of any other category. Based on 36-month rolling-window estimates, the autocorrelation has typically ranged between 0.2 and 0.6. It fluctuated sharply during the recent financial crisis, and most recently has become negative

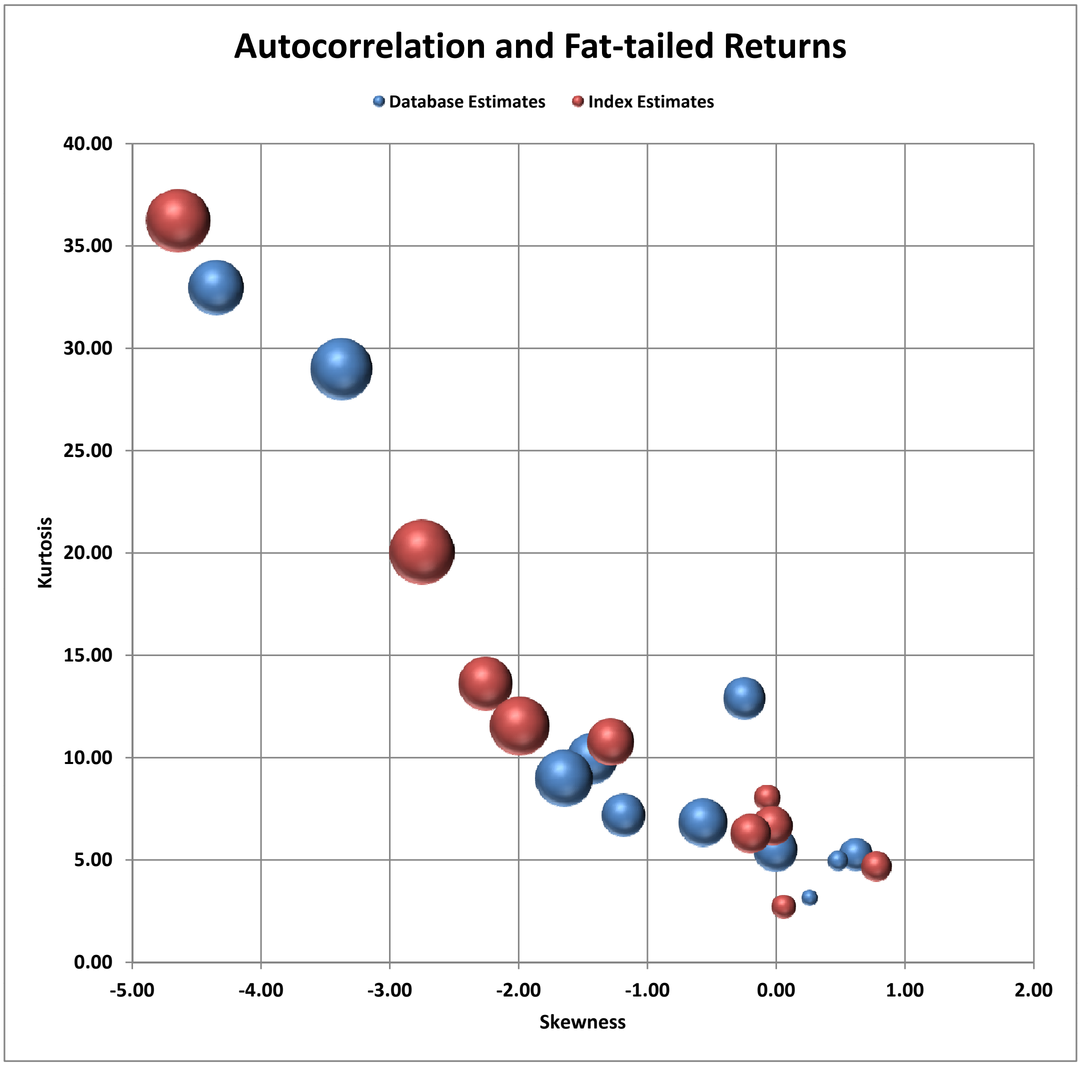
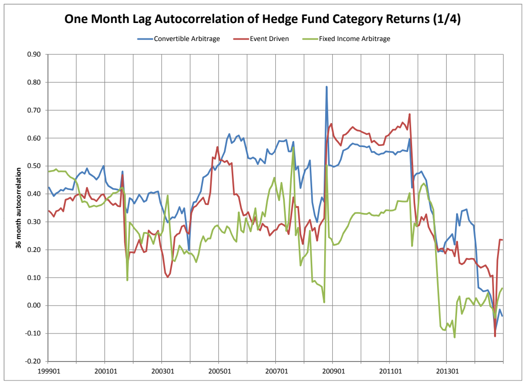
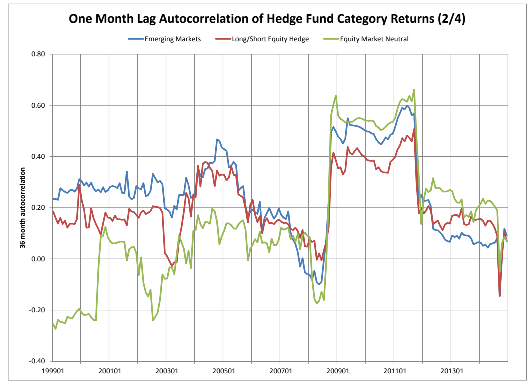


Figure 1: Autocorrelation and fat-tailed returns for funds in the Lipper TASS database and CS/DJ Hedge-Fund indexes. The location of each bubble reflects the skewness (x-axis) and kurtosis (y-axis) of a hedge-fund category. The size of each bubble reflects the corresponding category returns' autocorrelation. Results are provided for each category based on the average returns of funds in the Lipper TASS database and also based on the widely-used CS/DJ Hedge-Fund indexes.

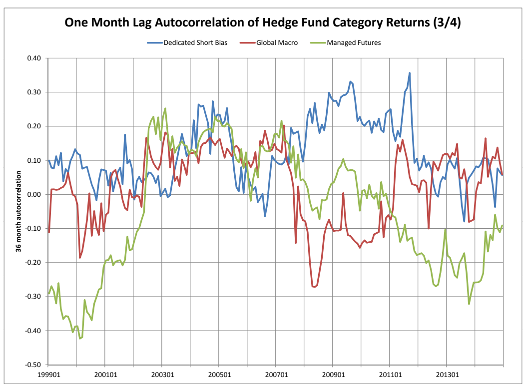
which has never happened before. Time will tell whether the autocorrelation structure reverts to its pre-crisis condition or has shifted to a lower "new normal".[14] We shall return to the subject of autocorrelation when we focus on measures of illiquidity risk in Section 5.



(a)



(b)



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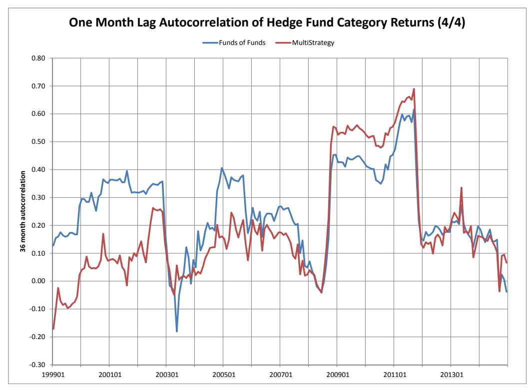


(d)

Figure 2: 36-month rolling-window autocorrelation for (a) Convertible Arbitrage, Event Driven, and Fixed Income Arbitrage; (b) Emerging Market, Long/Short Equity Hedge, and Equity Market Neutral; (c) Dedicated Short Bias, Global Macro, and Managed Futures; and (d) Fund of Hedge Funds and Multi-Strategy category returns from January 1996 through December 2014.

[14]We also show in Figure 4 that toward the end of the sample, the equity exposure of the Convertible Arbitrage strategy has shifted from positive to negative.

5 Illiquidity

Illiquidity is one of the most important characteristics of certain hedge fund investments that has only recently begun to receive the attention it deserves. Not only is illiquidity at the heart of most financial crises (see, for example, the discussion in Section 7), but it is also central to how many financial investments generate their returns. Taking on illiquidity risk is one of the most effective ways for long-horizon investors to build wealth, but it can also be the downfall of investors who are unaware of their illiquidity exposure and attempt to liquidate certain investments at the wrong time.

One of the biggest challenges to measuring illiquidity is the fact that there is currently no single definition of liquidity. The reason is simple: liquidity is not a one-dimensional characteristic, but has at least three distinct aspects to it. An asset is considered liquid if: (1) it can be bought or sold quickly; (2) the amount that can be bought or sold is large; and (3) buying or selling such large amounts will not adversely impact the market price. Certain assets may have one or two of these properties, but only truly liquid assets will have all three. For example, residential real estate can be sold quickly, but usually not without significant price concessions, hence this asset would not be considered liquid. What makes liquidity even harder to define is that these three characteristics are time- and context-dependent; what is liquid today may be highly illiquid tomorrow. A clear illustration of just how dynamic liquidity can be is the Quant Meltdown of August 2007, described in more detail in Section 7.1.

In Section 5.1, we review several measures of illiquidity that are specifically designed with hedge funds in mind. We consider the impact of illiquidity on statistical measures of hedge-fund performance such as volatilities, Sharpe ratios, and betas and how to correct for it in 5.2. Based on these and other measures of illiquidity, the magnitude of illiquidity risk premia in hedge-fund returns can be quantified, which we describe in Section 5.3. And in Section 5.4, we show how to incorporate measures of illiquidity into the traditional mean-variance portfolio optimization framework.

5.1 Measures of Illiquidity and Return Smoothing

The finance literature offers a number of theoretical and empirical measures of illiquidity including percentage bid/offer spreads (Tiniç (1972), Glosten and Milgrom (1985), Amihud and Mendelson (1986)), price impact (Kraus and Stoll (1972), Kyle (1985), Hasbrouck and Schwartz (1988), and Lillo, Farmer, and Mantegna (2003)), and volume-based statistics (Lo, Mamaysky, and Wang (2004), Lo and Wang (2006), and Pastor and Stambaugh (2003)).

However, these measures all assume the existence of a centralized exchange in which price discovery occurs regularly, that there exist designated market makers who post bids and offers, and that trading volume can be measured. As a result, none of these measures are applicable to investments in hedge funds, of which the vast majority are structured as privately placed securities.

Lo (2001) and Getmansky, Lo, and Makarov (2004) propose an alternate measure of illiquidity that depends only on asset returns, return autocorrelation, ρ_k:

$$\rho_k = \frac{\mathrm{Cov}[R_t, R_{t-k}]}{\mathrm{Var}[R_t]} \quad , \quad k > 0 \tag{1}$$

$$\hat{\rho}_k = \frac{(T-k+1)^{-1}\sum_{t=k-1}^{T}(R_t-\hat{\mu})(R_{t-k}-\hat{\mu})}{(T-1)^{-1}\sum_{t=1}^{T}(R_t-\hat{\mu})^2} \quad , \quad \hat{\mu} = T^{-1}\sum_{t=1}^{T} R_t \ . \tag{2}$$

In an efficient market, asset returns should be approximately serially uncorrelated, hence $\rho_k = 0$ for all $k > 0$—past returns should contain very little information about future returns, otherwise the information can be exploited via trading strategies that buy (shortsell) securities with positive (negative) return forecasts. The very process of exploiting this information will tend to reduce, if not eliminate entirely, any return autocorrelation. The only two reasons such information cannot be exploited and, therefore, eliminated, are: (1) if the autocorrelation is due to time-varying equilibrium expected returns; and (2) if the autocorrelation cannot be exploited due to trading frictions, i.e., illiquidity. The first possibility is less likely for shorter-horizon holding periods such as monthly or daily returns given the definition of equilibrium expected returns, hence the second possibility is the more likely explanation for significant return autocorrelation. In other words, returns may be autocorrelated because information about the underlying asset diffuses over time and investors with early access to this information cannot exploit it because the asset cannot be traded quickly, and/or cannot be traded in large size, and/or cannot be traded without moving the price significantly.

Getmansky, Lo, and Makarov (2004) construct a simple econometric model to estimate the degree of autocorrelation in hedge-fund returns by assuming that the true but unobservable economic return, R_t, of a hedge fund in period t satisfies a linear single-factor model:

$$R_t = \mu + \beta\Lambda_t + \epsilon_t \quad , \quad \mathrm{E}[\Lambda_t] = \mathrm{E}[\epsilon_t] = 0 \quad , \quad \epsilon_t \ , \ \Lambda_t \sim \mathrm{IID} \tag{3a}$$

$$\mathrm{Var}[R_t] \equiv \sigma^2 \tag{3b}$$

whereas the reported return R_t^o is:

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} \tag{4}$$

$$\theta_j \in [0,1] \ , \quad j = 0, \ldots, k \tag{5}$$

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k \tag{6}$$

which is a weighted average of the fund's true returns over the most recent $k+1$ periods, including the current period. True returns represent the flow of information that would determine the equilibrium value of the fund's securities in a frictionless market, and observed returns represent the results that the fund reports each month. Using maximum likelihood to estimate the smoothing parameters $\{\theta_j\}$, Getmansky, Lo, and Makarov (2004) confirm that funds with higher autocorrelation tend to be the more illiquid funds, e.g., emerging market debt, fixed income arbitrage, etc.

More generally, Khandani and Lo (2011b) establish a link between illiquidity and positive autocorrelation in asset returns among a sample of hedge funds, mutual funds, and various equity portfolios. For hedge funds, this link can be confirmed by comparing the return autocorrelations of funds with shorter vs. longer redemption-notice periods. They also document significant positive return-autocorrelation in portfolios of securities that are generally considered less liquid, e.g., small-cap stocks, corporate bonds, mortgage-backed securities, and emerging-market investments.

Getmansky, Lo, and Makarov (2004) and Bollen and Pool (2008) also observe that return autocorrelation may be evidence of return smoothing, the unsavory practice of reporting only part of the gains in the months when a fund has positive returns so as to partially offset potential future losses, thereby reducing volatility and improving risk-adjusted performance measures such as the Sharpe ratio (see Section 5.2). However, while large positive return autocorrelations should raise concerns regarding the potential of deliberate return-smoothing behavior, Getmansky, Lo, and Makarov (2004) emphasize that it is impossible to determine whether a fund is intentionally smoothing returns just from its return autocorrelations.

Bollen and Pool (2009) and Jylha (2011) show that hedge funds often push otherwise small negative returns above zero. Agarwal, Daniel, and Naik (2011) find evidence of manipulating reported returns upward in the month of December. Cici, Kempf, and Puetz (2015) use 13F filings to show that hedge-fund advisers strategically employ mismarking in stock positions to smooth their reported returns and push otherwise small negative returns above zero.

Aragon and Nanda (2015) link reporting delays to return smoothing, through reporting returns in "clusters". Patton, Ramadorai, and Streatfield (2013) find that hedge fund performance is lower among funds that have restated their return history to a database, especially among funds that show a high degree of monthly return autocorrelation. Ben-David, Franzoni, Landier, and Moussawi (2013) provide evidence suggesting that some hedge funds manipulate stock prices on critical reporting dates. They find that stocks in the top quartile of hedge fund holdings exhibit abnormal returns of 0.30% on the last day of the quarter and a reversal of 0.25% on the following day. A significant part of the return is earned during the last minutes of trading. Kruttli, Patton, and Ramadorai (2014) use an aggregate version of the liquidity measure of Getmansky, Lo, and Makarov (2004), estimated across a large set of hedge funds, and find that the measure has the ability to predict a large range of asset returns (commodities, currencies, bonds, and equities). The authors relate this finding to the role of hedge funds in liquidity provision in capital markets.

5.2 Illiquidity and Statistical Biases

Illiquidity can lead to a number of biases in the statistical properties of hedge-fund returns. For example, using a linear moving average time series model for illiquid hedge-fund returns, Getmansky, Lo, and Makarov (2004) show that standard estimators of volatility are biased downward, Sharpe ratios are biased upward, and the betas of regressions of hedge-fund returns on lagged market factors are non-zero. The authors find that after correcting for the effects of smoothed returns, some of the most successful types of funds tend to have considerably less attractive performance characteristics. Lo (2001) provides the appropriate correction term for computing volatilities and Sharpe ratios in these cases, and shows that corrected annualized Sharpe ratios based on monthly data can differ from the standard Sharpe ratio estimator by as much as 70%. Asness, Krail, and Liew (2001) show that in some cases where hedge funds purport to be market neutral, i.e., funds with relatively small market betas (market exposure) when only contemporaneous returns are used as regressors, including both contemporaneous and lagged market returns as regressors and summing the beta coefficients, yields significantly higher market exposure, implying a certain degree of illiquidity.

These empirical properties may have potentially significant implications for assessing the risks and expected returns of hedge-fund investments, including potential fraud detection.

5.3 Measuring Illiquidity Risk Premia

Suppose investors are given the choice between two assets that are identical in all respects but one: while one asset can be traded around the clock, the other asset can only be traded on the first Tuesday of each month. Most investors would choose the first (more liquid) asset. But when enough investors do this, the supply of the first asset may dwindle, and its price would rise relative to the second asset. At some point, investors will feel that the discount on the second asset—which yields a higher expected return today, assuming that its future expected payoff is unchanged—is sufficiently large to compensate them for the infrequency with which it can be traded, leading them to buy the second asset. The investors buying the second asset will obtain a higher expected return than investors in the first asset in exchange for accepting the risk that at the moment they want to sell their asset, it may not be possible to do so. This incremental return is called the "illiquidity premium".

Unfortunately, paired with the illiquidity premium is the illiquidity penalty: the periods when many owners want to sell are typically times during which few investors want to buy, so the asset's price may plummet beyond reason. In these circumstances it may be impossible to sell at a price near what an owner considers fair.

Liang (1999) and Aragon (2007) study the relation between hedge fund returns and a very specific form of illiquidity—lockup restrictions—and document a positive relationship between lockups and fund performance. Aragon (2007) finds that hedge funds with lockups have 4% to 7% per year higher excess returns than those of non-lockup funds (see Section 2.3 for further discussion of lockups and other share restrictions). Sadka (2010, 2012) shows that liquidity risk is an important determinant of the cross-sectional differences in hedge fund returns and concludes that hedge funds with significant liquidity risk subsequently outperform low-liquidity-risk funds by an average of 6% annually. Consistent with Brunnermeier and Pedersen (2009), Teo (2011) finds that hedge funds with strong incentives to raise capital, low manager option deltas, and no manager capital co-invested are more likely to take on excessive liquidity risk.

Using a sample of 2,927 hedge funds, 15,654 mutual funds, and 100 size- and book-to-market-sorted portfolios of U.S. common stocks, Khandani and Lo (2011b) construct autocorrelation-sorted long/short portfolios and conclude that illiquidity premia are generally positive and significant, ranging from 2.74% to 9.91% per year among the various hedge funds and fixed-income mutual funds. They do not find evidence for this premium among equity and asset-allocation mutual funds, or among the 100 U.S. equity portfolios. The time variation in their aggregated illiquidity premium shows that while 1998 was a difficult year for most funds with large illiquidity exposure, the following four years yielded significantly higher illiquidity premia that led to greater competition in credit markets, contributing to much lower illiquidity premia in the years leading up to the Financial Crisis of 2007–2009.

5.4 The Mean-Variance-Illiquidity Frontier

Modern portfolio theory implies that, to earn higher expected returns, an investor must bear higher systematic risk. While the historical time series evidence suggests that this is a good general guide (see, for example, Ibbotson, 2013), we believe that this model is too narrowly interpreted. Risk is generally thought of as the distribution of magnitudes of possible losses over a given time period. In a well-functioning market, this characterization should be conceptually adequate, even if, as a practical matter, obtaining a good estimate of risk is non-trivial. However, when markets break down, some assets cease to have a meaningful price—for a period of time, there may be no transactions at all. And if there are any sales, they are generally made by investors desperate for cash and willing to sell at fire-sale prices. The possibility of such temporary market failures is not captured very well by traditional risk measures. Nevertheless, it is a type of risk, and it stands to reason that investors willing to assume it should earn higher returns. Viewed this way, the illiquidity premium exists because illiquid assets carry extra risk, albeit of a unique sort.

We test this hypothesis by using data for the 19-year period from January 1996 through December 2014 and creating portfolios made up of three-month U.S. Treasury Bills, stocks, bonds, and any blend of our 11 average hedge-fund-style return series. Traditional mean-variance optimization would produce an efficient frontier that shows the best return one could have obtained for the indicated level of risk. In such an analysis, risk is typically proxied by the annualized standard deviation of the portfolio's returns. We generalize this framework to include a second nonlinear constraint: autocorrelation. The resulting three-dimensional surface based on volatility, return, and autocorrelation is depicted in Figure 3. Since return autocorrelation is often associated with portfolio illiquidity (see Section 5.1), constraining a portfolio to have low autocorrelation is likely to limit illiquidity risk and, consequently, also limit the amount of illiquidity premium in the portfolio. Figure 3 shows that this is exactly the case: to earn high returns in the period from 1996 through 2014, an investor would have had to bear the risk of ordinary market fluctuations (volatility), the risk of temporary market failure (illiquidity/autocorrelation), or a combination of both. The extra return that corresponds to the increased autocorrelation is as much as 2%, which is broadly consistent with other estimates of the illiquidity premium (Aragon (2007) and Sadka (2010, 2012)).

This analysis of the relationship between illiquidity and returns over the recent 19 years suggests that investors may benefit from determining their tolerance for illiquidity alongside

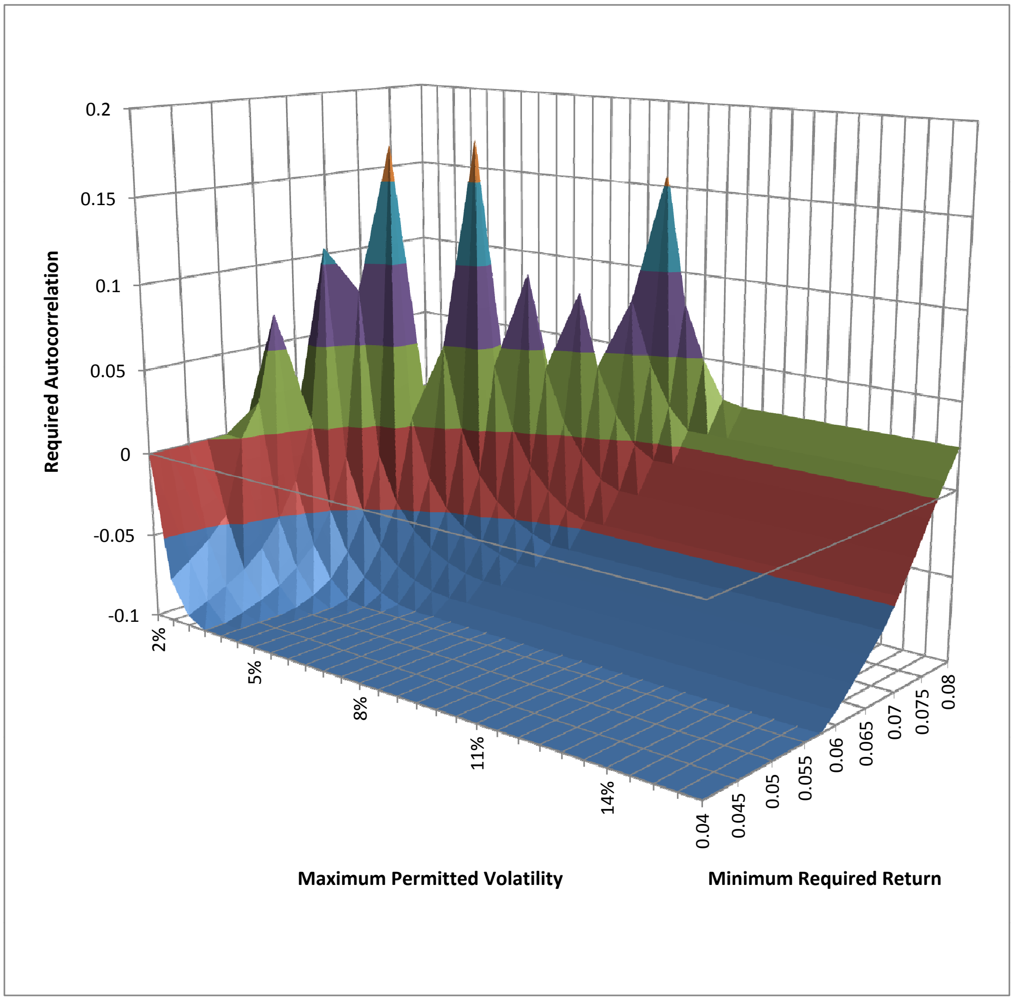


Figure 3: The return/volatility/autocorrelation surface for the optimal allocation among cash, stocks, bonds, and hedge-fund-category indexes, using data from January 1996 through December 2014. To help visualize the z-axis, colored bands have been overlaid on the surface; where the required return can be achieved with very low autocorrelation, the surface is colored blue. As the necessary autocorrelation increases, the surface color becomes red, green, purple, cyan, and orange.

their tolerance for traditional risk and choosing their asset allocation accordingly. Table 6 shows the striking differences in autocorrelation among hedge fund categories; it is possible that the highly autocorrelated categories present investors with a greater opportunity to earn the illiquidity premium while less autocorrelated categories present investors with more protection against downside surprises due to market failures.

6 Hedge Fund Risks

What risks do hedge funds take and do they earn expected returns commensurate with those risks? Understanding the answers to these two questions is crucial for any investor seeking to determine whether a hedge fund investment would be a prudent addition to her portfolio. The traditional investment framework of the Sharpe-Lintner Capital Asset Pricing Model (CAPM) provides a natural starting point. Do hedge-fund expected returns exhibit any alpha, i.e., do they exceed their risk-adjusted cost of capital where the risk adjustment is with respect to their equity beta?

In many cases, the answer to this narrow question is yes, but there is a concern among academics and hedge-fund investment professionals that a portion of this alpha may be attributed to exposures to factors other than the stock market, e.g., other asset classes such as commodities, currencies, and real estate. Moreover, many once-unique investment strategies pioneered by the hedge-fund industry have become commoditized. For example, the carry-trade, size-spread, and trend-following strategies are all so well-understood that retail investors can now invest in them through ETFs and mutual funds that use mechanical trading strategies.[15] Exposures to all these well-understood drivers of returns may now be thought of as "alternative" or "exotic" betas. Therefore, hedge-fund expected returns are inextricably intertwined with the risk exposures associated with hedge-fund strategies. Measuring and managing these exposures is the focus of this section.

In Section 6.1 we review how risk is measured and how hedge-fund managers adjust their risk-taking in response to incentives. In Section 6.2 we discuss the use of linear factor models, a common risk analysis tool that enables the user to estimate not only how much risk is being taken, but also what kind of risk is being taken, even in the absence of portfolio transparency. As useful as these models are, they have important limitations and in Section 6.3 we provide a specific example of how they can yield misleading results if used improperly.

In Section 6.4 we continue our focus on hedge fund risks, turning from market-based risks to operational risks; in section Section 6.5 we describe how investors and hedge fund

[15] For a comprehensive guide to ETFs, see Hill, Nadig, and Hougan (2015).

managers manage the risks associated with hedge fund investing. In Section 6.6 we conclude our discussion of hedge fund risks with the natural follow-on topic of hedge fund replication.[16] As some aspects of hedge fund investing have become well-understood, investor demand has grown for cheaper access to alternative betas. Hedge-fund replication strategies built to meet this demand now invest billions of dollars around the world.

6.1 VaR and Risk-Shifting

Because of the heterogeneity and inherent nonlinearities of hedge-fund strategies, a natural starting point for risk management in the hedge-fund industry is Value-at-Risk (VaR), a concept that originated in the derivatives industry. Instead of adopting the traditional mean-variance framework of the investment management industry, derivatives traders and their risk managers focus on estimating the likelihood of extreme losses over a given investment horizon. If the daily change in the value of a portfolio is given by the random variable X_t, then the 5% one-day VaR of this portfolio is defined to be value $K>0$ such that

$$\text{Prob}(X_t \leq -K) \quad = \quad 5\% \; . \tag{7}$$

By specifying a limit on K, investors and managers can control the amount of risk in their portfolios. Of course, doing so requires the distribution of X_t which involves statistical inference as well as considerable knowledge of the underlying strategies that generate X_t.

Jorion (2007) illustrates how VaR methods can be used to measure and control the market risk of hedge funds. Gupta and Liang (2005) examine the risk characteristics and capital adequacy through the VaR approach. They find that as of March 2003, 3.7% of live funds and 10.9% of defunct funds were under-capitalized. Jorion (2008) develops methods to measure the forward-looking risk of portfolios exposed to corporate events such as restructurings, bankruptcies, mergers, acquisitions, or other special situations. Using both TASS and HFR databases, Bali, Gokcan, and Liang (2007) find that live funds with high VaR outperform those with low VaR by 9% annually. On the other hand, the relationship between downside risk and expected returns is negative for defunct funds. However, using the TASS database Liang and Park (2007) describe shortcomings of VaR and find that other left-tail risk measures such as Expected Shortfall and Tail Risk can be superior in explaining the cross-sectional variation in hedge fund returns.

Brown, Goetzmann, and Park (2001) investigate risk-shifting in hedge funds, and find

[16] In the interest of full disclosure, two of the authors of this review—P. Lee and A. Lo—have commercial interests in a hedge-fund beta replication mutual fund.

evidence of tournament behavior among funds. Specifically, funds that exhibit good performance during the first half of the year tend to reduce the volatility of their portfolios during the second half, and vice versa for funds that perform poorly during the first half of the year. Agarwal, Daniel, and Naik (2002) also report this finding for hedge funds, using an alternative method in high-water mark estimation. Hodder and Jackwerth (2007) analyze the effect of incentive fees, high-water marks, and managerial ownership of shares on hedge fund risk-taking. In a related paper, Panageas and Westerfield (2009) challenge the basic intuition that convex compensation schemes—where managers are rewarded for gains but not punished for losses—increase risk-taking. Convex payoffs are common in hedge fund contracts, and the authors show that in an infinite-horizon setting, even a risk-neutral manager will not take unbounded risks. As a result, the incentive to take greater risk depends on the interaction between convexity and finite horizons, not just on convex compensation structures.

Using the Zurich hedge fund universe, Kouwenberg and Ziemba (2007) test the relation between risk taking and incentive fees. They find that loss averse managers increase the risk of the fund's investment strategy with higher incentive fees. However, risk taking is greatly reduced if a substantial amount of the manager's own money (at least 30%) is in the fund. Aragon and Nanda (2012) find that when hedge funds are likely to be liquidated, and therefore managers do not expect to operate the funds for many periods, high-water marks are far less effective in moderating risk-shifting following poor performance. Goetzmann, Ingersoll, and Ross (2003) provide a closed-form solution to the high-water mark contract under certain conditions. This solution shows that managers have an incentive to take risks.

6.2 Linear Factor Models

A more refined approach to risk management for hedge funds is to approximate a fund's return R_{pt} by a linear factor model:

$$R_{pt} \; = \; \alpha_p \, + \, \beta_{p1} F_{1t} \, + \, \cdots \, + \, \beta_{pK} F_{Kt} \, + \, \epsilon_{pt} \tag{8}$$

where the factors $\{F_{it}\}$ are observable explanatory variables such as stock and bond indexes or the returns of well-defined algorithmic strategies such as trend-following, mean-reversion, or carry-trade strategies. Such factor models are especially useful for answering questions about the likely impact of various scenarios on a hedge fund's returns, e.g., how will a specific hedge fund's return be affected if the stock market declines by 10%?; how sensitive is it to interest-rate fluctuations?; does the hedge fund employ momentum strategies?

The unexplained components of (8) are attributable to three sources: alpha (the unique investment skills of the hedge-fund manager), omitted factors, and idiosyncratic returns. The portion of the returns explained by the factors is generally referred to as beta(s), which comes from the traditional Sharpe-Lintner CAPM investment framework.

Linear factor models can provide insight into the intrinsic characteristics and risks of a hedge fund's investments and how they vary across time and circumstances. For example, Titman and Tiu (2011) regress individual hedge fund returns on several risk factors and show that hedge funds with low R^2's with respect to these factors tend to have higher Sharpe ratios. On the other hand, Asness, Krail, and Liew (2001) use linear factor models to show that certain hedge funds that claim to be market neutral are not, containing highly significant lagged exposure to the S&P 500 which is a symptom of illiquidity (see Section 5).

The usefulness of linear factor models is determined largely by the choice of factors, and many studies have contributed to our understanding of types of factors that are most relevant for hedge-fund applications.[17] As a result, many linear factor models have been proposed for hedge funds, and the sheer number of published studies on this topic is a reflection of the heterogeneity of the hedge-fund industry as well as the complexity and nonlinearity of the returns that are being approximated by linear models.[18] Several authors have suggested using more easily interpretable factors such as fund characteristics and simple indexes.[19] The sensitivity of a fund's value to a broad-based gauge of asset-class returns in a well-known category such as stocks is sometimes called "traditional beta", while the sensitivities of a fund's returns to less-well-known factors such as the returns on lookback-straddles or mechanical carry-trade strategies are often called "exotic betas" or "alternative betas" (Roncalli and Teiletche (2008)). In recent years a number of ETFs and mutual funds have launched with the aim of providing investors access to some of these alternative betas (see Section 6.6).

These methods for selecting easily interpretable factors exhibit varying degrees of success depending on the nature of the hedge-fund strategies to which they are applied, but they are generally preferred to purely statistical approaches such as PCA, which Fung and Hsieh (1997) use to extract factors from the covariance matrix of their sample of 409 hedge funds

[17]Examples of linear factor models for hedge funds include Fung and Hsieh (1997, 2002, 2004), Liang (1999, 2004), Agarwal and Naik (2004), Bondarenko (2004), Chan, Getmansky, Haas, and Lo (2004, 2006, 2007), Bali, Brown, and Caglayan (2011, 2012), and Buraschi, Kosowski, and Trojani (2015).

[18]For example, Fung and Hsieh (2001), Mitchell and Pulvino (2001), and Agarwal and Naik (2004) have empirically documented nonlinear relationships between hedge-fund and market returns, and Lo (1999) provides a simple analytical example of a nonlinear hedge-fund strategy consisting of shorting out-of-the-money put options on S&P 500 index futures.

[19]See Schneeweis and Spurgin (1998), Liang (1999), Edwards and Caglayan (2001), and Capocci and Hubner (2004).

and CTAs.

To develop some intuition for linear factor models applied to hedge funds, consider Fung and Hsieh's (2001) seven-factor model consisting of bond-trend, currency-trend, commodity-trend, equity-market, size-spread, bond-market, and credit-spread factors.[20] The first three factors are the returns of lookback straddles that capture the idea that trend-following funds find profit opportunities in large market moves in several asset classes. The equity-market factor is simply the return of the S&P 500 total return index, while the size-spread factor is the outperformance of small caps relative to large caps (Russell 2000 vs. S&P 500). The bond-market factor is the change in yield of the U.S. 10-year bond and is thus inversely related to returns on an investment in the same. The credit-spread factor is the difference between the changes in the yield on Baa-rated debt and the yield on U.S. Treasuries. Roughly speaking, this factor is inversely related to the return on a strategy of buying high yield debt while shorting U.S. Treasuries.

To illustrate how linear factor models might be used in practice, we regress our set of average hedge fund category returns on the Fung and Hsieh (2001) seven factors over two time periods: January 1996 through December 2014 (Table 7) and January 2006 through December 2014 (Table 10).[21] The results in Table 7 suggest that the equity-market, size-spread, and credit-spread factors are linked to the returns of many hedge fund categories. For example, the "All Single Manager Funds" row suggests that from 1996 through 2014 the average hedge fund portfolio included investments that behaved like stocks (especially small cap stocks) and high yield debt. The results in Table 7 also suggest that some funds behaved more idiosyncratically. For example, Managed Futures and Global Macro funds are associated with investment strategies that rely on currency and commodity straddles, and Equity Market Neutral funds are associated with a relative value (long small caps, short large caps) strategy.

Although linear factor models like Fung and Hsieh's (2001) are able to capture historical relationships between hedge funds and risk factors, they may not be ideal for practical purposes such as risk management. In particular, four of the seven factors in Fung and Hsieh (2001) do not have liquid futures contracts associated with them (the three lookback straddles and the credit spread); hence, if an investor wishes to reduce exposure to one of these factors, it would be difficult to do so. Second, the large number of factors increases the potential for overfitting and, therefore, implies less effective out-of-sample performance.

[20] The data for Fung and Hsieh's (2001) seven factors is located at `http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls`.

[21] We use bond data from the Federal Reserve and stock data from Bloomberg (SPTR Index and RU30INTR Index).

	Annualized Category Volatility	R Squared	Monthly Alpha	Bond Trend Following Factor	Currency Trend Following Factor	Commodity Trend Following Factor	Equity Market Factor	Size Spread Factor	Bond Market Factor	Credit Spread Factor
Annualized Factor Volatility	N/A	N/A	N/A	*51.4%*	*63.4%*	*50.1%*	*15.4%*	*11.8%*	*92.6%*	*76.9%*
Convertible Arbitrage	*7.3%*	0.58	0.332%*	-0.014*	-0.003	-0.010	0.114*	0.055	-0.020*	-0.061*
Dedicated Short Bias	*15.6%*	0.62	0.557%*	-0.022	0.000	-0.006	-0.722*	-0.410*	-0.013	-0.009
Emerging Markets	*14.2%*	0.52	0.181%	-0.041*	0.015	-0.006	0.468*	0.210*	-0.010	-0.047*
Equity Market Neutral	*3.3%*	0.24	0.333%*	-0.012*	0.002	-0.002	0.037*	0.054*	-0.001	-0.010*
Event Driven	*5.9%*	0.67	0.391%*	-0.020*	0.003	-0.008	0.167*	0.120*	-0.004	-0.029*
Fixed Income Arbitrage	*4.4%*	0.43	0.374%*	-0.010*	-0.007	0.000	0.009	0.019	-0.018*	-0.039*
Global Macro	*5.2%*	0.24	0.310%*	-0.008	0.024*	0.015*	0.100*	0.009	-0.015*	-0.017*
Long/Short Equity Hedge	*9.0%*	0.72	0.322%*	-0.003	0.009	0.003	0.388*	0.300*	-0.002	-0.014*
Managed Futures	*9.4%*	0.23	0.389%*	0.016	0.033*	0.048*	0.051	0.070	-0.019*	-0.003
Multi-Strategy	*5.2%*	0.43	0.339%*	-0.003	-0.003	0.006	0.156*	0.100*	-0.006	-0.016*
Fund of Funds	*6.0%*	0.46	0.147%	-0.011	0.010	0.007	0.185*	0.113*	-0.008*	-0.022*
All Single Manager Funds	*6.3%*	0.66	0.304%*	-0.008	0.010*	0.007	0.246*	0.161*	-0.008*	-0.022*
Correl. w/ Equity Factor	N/A	N/A	N/A	-0.23	-0.21	-0.17	1.00	0.08	0.22	-0.44

Table 7: Conditional exposures of average hedge fund category returns to the seven Fung and Hsieh (2001) factors. The exposures for the 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database are based on a multivariate regression with a constant term. Regression outputs that are significant with 95% confidence are indicated by "*" and shown in color (orange for negative and blue for positive). Monthly correlations between hedge fund returns and all seven factors are presented. This analysis spans January 1996 through December 2014.

In contrast, consider a more parsimonious four-factor model that is very nearly investable. Two factors are the same as in Fung and Hsieh (2001): the equity-market and size-spread factors, and one is similar: a bond-market factor (we use the Barclays U.S. Aggregate Bond Index). We also add an additional factor, 2-to-3 month lagged returns of the S&P 500, to capture illiquidity exposure, as documented by Asness, Krail, and Liew (2001).[22] The estimates are presented in Table 8. For the average hedge fund, this model has about the same in-sample R^2 as Fung and Hsieh's (2001) model despite its greater parsimony, though for specific categories it often falls slightly short for lack of some of the non-investable factors present in Fung and Hsieh (2001).

	Annualized Category Volatility	**R Squared**	**Monthly Alpha**	*Equity Market Factor*	*Lagged Equity Market Factor*	*Size Spread Factor*	*Bond Market Factor*
Annualized Factor Volatility	N/A	N/A	N/A	*15.4%*	*11.4%*	*11.8%*	*3.5%*
Convertible Arbitrage	*7.3%*	0.34	0.01%	0.23*	0.13*	0.12*	0.33*
Dedicated Short Bias	*15.6%*	0.62	0.38%	-0.70*	0.05	-0.39*	0.38*
Emerging Markets	*14.2%*	0.47	0.01%	0.57*	0.14*	0.27*	0.10
Equity Market Neutral	*3.3%*	0.25	0.25%*	0.06*	0.08*	0.07*	0.02
Event Driven	*5.9%*	0.61	0.21%*	0.24*	0.16*	0.15*	0.07
Fixed Income Arbitrage	*4.4%*	0.22	0.11%	0.08*	0.11*	0.05*	0.35*
Global Macro	*5.2%*	0.16	0.10%	0.09*	0.08*	0.02	0.38*
Long/Short Equity Hedge	*9.0%*	0.72	0.20%	0.41*	0.09*	0.31*	0.07
Managed Futures	*9.4%*	0.05	0.17%	-0.03	0.02	0.05	0.58*
Multi-Strategy	*5.2%*	0.42	0.20%*	0.18*	0.08*	0.11*	0.14
Fund of Funds	*6.0%*	0.45	-0.03%	0.21*	0.12*	0.13*	0.19*
All Single Manager Funds	*6.3%*	0.64	0.14%	0.27*	0.09*	0.18*	0.17*
Correl. w/ Equity Factor	N/A	N/A	N/A	1.00	0.04	0.08	-0.01

Table 8: Conditional exposures of average hedge fund category returns to four investable factors. The exposures for the 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database are based on a multivariate regression with a constant term. Regression outputs that are significant with 95% confidence are indicated by "*" and shown in color (orange for negative and blue for positive). Monthly correlations between hedge fund returns and all four factors are presented. This analysis spans January 1996 through December 2014.

[22]While lagged exposure to stocks is not traditionally considered an investable factor, one could, of course, simply add a corresponding exposure to the S&P 500 to obtain a substantively similar portfolio.

For practical purposes, investors and managers are most interested in forecasting a fund's future risks. Accordingly, we also evaluate the funds' out-of-sample fit for each linear factor model using a 24-month rolling window and one-month-ahead predictions. The results are reported in Table 9, which shows that in the out-of-sample period, the simpler model does a better job for seven of the 10 hedge fund categories. This suggests that, except where specialized factors dominate a fund's returns (e.g., the credit spread), the best linear factor model forecast of a hedge fund's future risk may be obtained from simpler, investable factors.

Out-of-sample R2	**Fung & Hseih 7-factor Model**	**Investable 4-factor Model**
Convertible Arbitrage	0.49	0.31
Dedicated Short Bias	0.57	0.66
Emerging Markets	0.36	0.45
Equity Market Neutral	-0.06	0.14
Event Driven	0.52	0.56
Fixed Income Arbitrage	0.14	0.13
Global Macro	-0.39	-0.20
Long/Short Equity Hedge	0.62	0.71
Managed Futures	-0.13	-0.22
Multi-Strategy	0.28	0.44
Fund of Funds	0.26	0.33
All Single Manager Funds	0.54	0.62

Table 9: Out-of-sample analysis for the period 1998–2014. Comparison between the four-factor investable model and the seven-factor Fung and Hsieh (2001) model. For each category, the better-performing model is marked in blue.

Table 10 contains conditional risk-adjusted exposures of average hedge fund category returns to the seven Fung and Hsieh (2001) factors during the period from January 2006 through December 2014. These exposures suggest an interesting difference between the recent nine years and the preceding period: hedge funds no longer have a positive exposure to the size-spread factor. This implies that, while hedge funds generally maintained their exposure to stocks and the credit spread, on average they stopped holding long small-cap/short large-cap relative-value positions. Given funds' historical preference for small-cap stocks, this change may reflect a significant change within the industry and could be a direction for further research. This result is supported by Table 11 where, in the context of the four-factor investable model, hedge funds' recent exposure to the size-spread factor again is seen to have dwindled to insignificance or become negative.

	Annualized Category Volatility	R Squared	Monthly Alpha	Bond Trend Following Factor	Currency Trend Following Factor	Commodity Trend Following Factor	Equity Market Factor	Size Spread Factor	Bond Market Factor	Credit Spread Factor
Annualized Factor Volatility	N/A	N/A	N/A	*52.7%*	*67.6%*	*54.3%*	*15.3%*	*8.6%*	*90.1%*	*95.3%*
Convertible Arbitrage	*9.5%*	0.70	0.132%	-0.013	-0.004	-0.021	0.150*	-0.031	-0.021*	-0.069*
Dedicated Short Bias	*9.9%*	0.59	0.209%	-0.004	0.009	-0.009	-0.347*	-0.281*	-0.012	0.009
Emerging Markets	*11.6%*	0.67	-0.069%	-0.030	0.017	-0.017	0.426*	-0.070	-0.011	-0.046*
Equity Market Neutral	*3.5%*	0.56	0.154%*	-0.008	-0.003	-0.005	0.094*	-0.050	0.005	-0.011*
Event Driven	*6.4%*	0.76	0.238%*	-0.015*	0.002	-0.018*	0.189*	0.009	0.005	-0.026*
Fixed Income Arbitrage	*4.9%*	0.69	0.183%*	-0.006	-0.008	-0.010	0.090*	-0.080*	-0.016*	-0.034*
Global Macro	*3.7%*	0.28	0.373%*	0.007	0.006	0.009	0.121*	-0.050	0.004	-0.005
Long/Short Equity Hedge	*7.4%*	0.77	0.140%	-0.009	0.007	-0.007	0.305*	0.068	0.004	-0.021*
Managed Futures	*8.6%*	0.21	0.425%	0.025	0.016	0.048*	0.148*	-0.104	0.008	0.011
Multi-Strategy	*4.8%*	0.60	0.146%	-0.003	-0.003	0.000	0.152*	-0.052	0.001	-0.020*
Fund of Funds	*5.2%*	0.54	-0.016%	-0.007	0.004	-0.001	0.166*	-0.053	0.002	-0.019*
All Single Manager Funds	*5.8%*	0.70	0.179%	-0.005	0.005	-0.001	0.225*	-0.019	0.000	-0.022*
Correl. w/ Equity Factor	N/A	N/A	N/A	-0.36	-0.31	-0.23	1.00	0.40	0.29	-0.55

Table 10: Conditional risk-adjusted exposures of average hedge fund category returns to the seven Fung and Hsieh (2001) factors. The exposures for the 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database are based on a multivariate regression with a constant term. Regression outputs that are significant with 95% confidence are indicated by "*" and shown in color (orange for negative and blue for positive). Monthly correlations between hedge fund returns and all seven factors are presented. This analysis spans January 2006 through December 2014.

	Annualized Category Volatility	**R Squared**	**Monthly Alpha**	*Equity Market Factor*	*Lagged Equity Market Factor*	*Size Spread Factor*	*Bond Market Factor*
Annualized Factor Volatility	N/A	N/A	N/A	*15.3%*	*11.8%*	*8.6%*	*3.2%*
Convertible Arbitrage	*9.5%*	0.43	-0.36%	0.35*	0.16*	0.04	0.62*
Dedicated Short Bias	*9.9%*	0.57	0.17%	-0.40*	-0.02	-0.29*	0.28
Emerging Markets	*11.6%*	0.60	-0.40%	0.56*	0.16*	-0.02	0.38
Equity Market Neutral	*3.5%*	0.52	0.08%	0.15*	0.09*	-0.03	-0.07
Event Driven	*6.4%*	0.67	0.04%	0.29*	0.17*	0.05	0.00
Fixed Income Arbitrage	*4.9%*	0.45	-0.11%	0.18*	0.11*	-0.04	0.43*
Global Macro	*3.7%*	0.22	0.36%*	0.12*	-0.01	-0.05	-0.03
Long/Short Equity Hedge	*7.4%*	0.72	0.04%	0.38*	0.07*	0.09	-0.05
Managed Futures	*8.6%*	0.02	0.47%	0.04	-0.01	-0.15	-0.11
Multi-Strategy	*4.8%*	0.55	-0.01%	0.21*	0.12*	-0.03	0.06
Fund of Funds	*5.2%*	0.52	-0.16%	0.22*	0.12*	-0.03	0.02
All Single Manager Funds	*5.8%*	0.65	0.02%	0.29*	0.09*	0.00	0.08
Correl. w/ Equity Factor	N/A	N/A	N/A	1.00	0.11	0.40	0.06

Table 11: Factor analysis based on the four-factor investable model over the period from January 2006 through December 2014. Factor loadings that are significant with 95% confidence are indicated by "*" and shown in color (orange for negative and blue for positive).

6.3 Limitations of Hedge-Fund Factor Models

As useful as linear factor models are for capturing the risks and rewards of hedge-fund returns, these models have their limitations and there are reasons to be cautious in their use:

(i) **Correlation vs. causation:** The fact that a combination of well-understood factors may have similar patterns of gains and losses to a given hedge fund does not necessarily mean that the hedge fund's strategy is based on those factors. Correlation need not imply causation, but could be the result of chance, overfitting, or some common latent factor.

(ii) **Approximate fit:** A factor model usually explains only part of the hedge funds' returns, and even that part is typically overfit because of a mismatch between the explanatory factors and the true contents of the hedge fund portfolio.

(iii) **Nonstationarity:** Even if a factor model accurately explains a fund's returns, the risks associated with every hedge fund change over time, albeit often slowly. So a factor model rarely predicts the future as well as it explains the past.

(iv) **Non-investability:** In general, a researcher cannot consider the returns of every combination of well-understood factors to be an alternative to investing in the indicated hedge fund, as the factors may not be investable. A combination of factors might not be investable for many reasons. For example, one cannot invest $1 billion in the Case-Shiller Atlanta housing index, even though using the index in a factor model might provide insight into the intrinsic properties of the hedge fund's portfolio. Even simple factors like stock market indexes are not entirely investable (though they are very nearly so) because accessing them incurs commissions, management fees, and/or tracking error.

Several of these weaknesses are manifest in the following example, which involves two categories of hedge funds that focus on relative value bets, often using illiquid fixed income instruments: Fixed Income Arbitrage and Convertible Arbitrage. With a 12-month window, we use a univariate factor model to estimate the exposure of each category to the S&P 500 index (see Figure 4). At first this is low, as one would expect in strategies like these. But in the Fall of 2008, the estimated sensitivity of these funds' returns to those of the S&P 500 spikes dramatically. A naïve interpretation of the results might be that the average fund manager in both of these categories decided to buy a large quantity of equities. But it seems unlikely that so many managers of low-volatility relative-value strategies would suddenly boost risk and take directional bets. A more plausible alternative is that, although the assets in the funds' portfolios usually exhibit a relatively placid return profile, during the crisis their prices swung sharply as plunging equity prices forced synchronous fire-sales of illiquid assets (Khandani and Lo (2007)). This type of synchronized behavior seems to be a more plausible driver of the covariation reported in Figure 4.

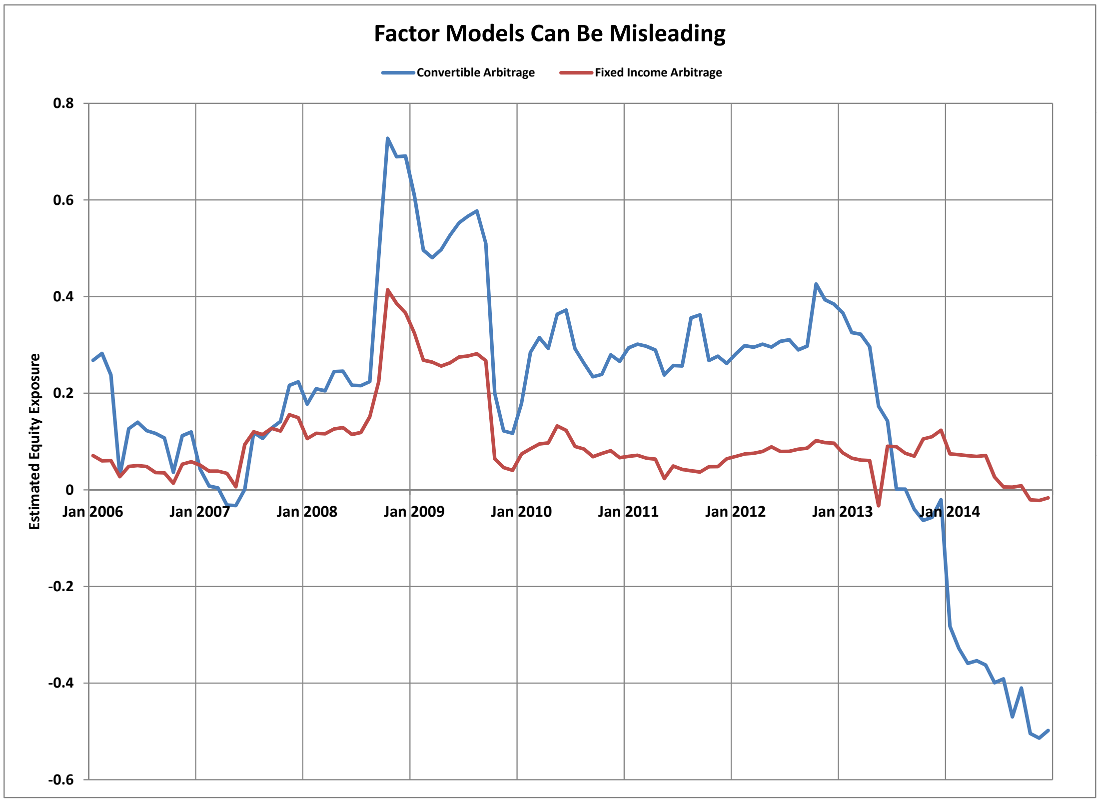


Figure 4: Time-varying exposures to the S&P 500 for Convertible Arbitrage and Fixed Income Arbitrage styles from January 2006 through December 2014. Trailing 12-month S&P 500 betas from a univariate factor model are graphed.

The most common approach to addressing nonlinearities in hedge-fund returns is to use factors that exhibit similar kinds of nonlinearities. For example, Fung and Hsieh (2001) create "style factors" that embed option-like characteristics of hedge funds. Similarly, Agarwal and Naik (2004) propose option-based risk factors consisting of highly liquid at-the-money and out-of-the-money call and put options for analyzing dynamic risk exposures of hedge funds. Agarwal and Naik (2004) suggest using piecewise linear models to study market risk for hedge fund returns. Fung and Hsieh (1997, 2001, 2004) introduce nonlinearity in factor returns by dividing monthly returns of each asset class (excluding cash) into five "states" to capture trading dynamics of hedge-fund styles. Billio, Getmansky, and Pelizzon (2012) propose a regime-switching beta model to measure dynamic risk exposures of hedge funds to various risk factors during different market volatility conditions. Bondarenko (2004) and Buraschi, Kosowski and Trojani (2015) introduce and analyze variance and correlation risk factors for hedge funds. Roncalli and Weisang (2010) apply advanced Bayesian filters' algorithms, known as particle filters, to capture nonlinearities documented in hedge fund returns (see Section 6.6 for a more detailed discussion in the context of hedge-fund beta replication). And Patton and Ramadorai (2013) introduce a new econometric methodology to capture nonlinearities and time-series variation in hedge funds' exposures to risk factors using high-frequency data, and find that these exposures vary significantly across months. Diez de los Rios and Garcia (2011) show that nonlinearities are important for some strategies, but not for the entire hedge-fund industry. Cai and Liang (2012a,b) use rolling-window OLS and Kalman filtering/smoothing to study non-linearities in hedge fund returns.

6.4 Operational Risks

Due to the complexities of proprietary trading, the lack of transparency, and the lack of regulatory oversight, hedge funds are especially exposed to operational risk, defined by the Basel Committee on Banking Supervision as "the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events". Feffer and Kundro (2003) were perhaps the first to call attention to this important source of risk, noting that half of all hedge-fund failures can be attributed to operational risk alone. They observe that "the most common operational issues related to hedge fund losses have been misrepresentation of fund investments, misappropriation of investor funds, unauthorized trading, and inadequate resources" (Feffer and Kundro, 2003, p. 5). They report that only 6% of their sample involved inadequate resources, whereas 41% involved misrepresentation of investments, 30% involved misappropriation of funds, and 14% involved unauthorized trading.

Since then, a number of studies have focused on operational risk. For example, Gupta and Kazemi (2007) study the failure of the $9 billion hedge fund Amaranth Advisors and conclude that operational issues were a key factor in this fund's demise. In a series of papers, Brown, Goetzmann, Liang, and Schwarz (2008, 2009, and 2012) develop several quantitative models for measuring operational risk in managed funds. Using a complete and unique SEC ADV filing dataset, they find that operational risk (represented by past legal or regulatory problems) is significantly related to the use of leverage, fund ownership structure, and conflict-of-interest issues. Higher operational risk funds tend to have relatively low leverage because of strict scrutiny from lenders, more concentrated ownership, and severe conflict-of-interest problems. Through a canonical correlation analysis, they map the ADV information to the regular fund information such as assets, returns, volatility, fees, leverage, and share restrictions, which, in turn, they use to construct an omega-score model to predict future fund performance and attrition. Consistent with the Basel definition, they find that the higher the omega score, the lower the future performance and the higher the probability of attrition.

Brown, Goetzmann, Liang, and Schwarz (2012) use finer information on the individual funds to quantify operational risk. Based on 444 proprietary due diligence reports, they are able to show that operational risk is directly related to inadequate or failed internal processes, represented by internal pricing of the portfolio, lack of reliability on reputable auditors and institutional quality signatures, and frequent misrepresentation of past problems or fund characteristics. The quantitative model based on these variables sharply predicts future fund performance and fund disappearance. However, the risk-flow analysis indicates that investors either ignore the operational risk issues or are ignorant of them, which further validates the importance of mandatory disclosure of fund information and information verification.

They also find that hedge funds that have experienced legal problems are less likely to use independent pricing agents and are more likely to have switched pricing agents within the past year, allowing these hedge funds greater pricing discretion. This discretion is a potential concern because, as Cassar and Gerakos (2011) show, hedge funds with less verifiable pricing sources and greater pricing discretion for their managers report smoother returns, resulting in misleading volatility and Sharpe ratio estimates (see Section 5.1). Bollen and Pool (2012) link the incidence of SEC lawsuits to suspicious patterns in reported returns, and find that the discontinuity in a fund's return distribution (some funds push returns above zero) is a reliable predictor of subsequent charges of misreporting brought by the SEC.

Ozik and Sadka (2014) argue that hedge funds offer informational advantages to managers over their clients through fund flows. They demonstrate that fund flows predict returns and find evidence that managers front-run their clients using this information.

On a more positive note, Brown, Fraser, and Liang (2008) argue that due diligence is an important source of alpha for diversified hedge fund portfolios. Effective due diligence can eliminate or reduce problematic funds and avoid future losses resulting from operational risk. However, due diligence is an expensive process; there is a significant competitive advantage to sufficiently large funds of funds, which are able to absorb this fixed and necessary cost. In contrast to hedge funds, the authors find significant economies of scale for funds of funds—the larger the fund of funds, the better its performance.

6.5 Risk Management

The previous sections' discussions highlight the fact that hedge funds have more complex and dynamic risk exposures than traditional investments. Therefore, proper risk management protocols are essential from both investors' and managers' perspectives. The old adage "a good way to make money is not to lose it in the first place" is particularly relevant for hedge funds given the active bets they make and the critical role that risk management plays in generating their returns. Moreover, with reliable estimates of risk exposures from a linear factor model, it is possible for investors to hedge certain risks that they wish to reduce, and accentuate other risks that they are especially keen to take on.

This is the motivation for Healy and Lo's (2009) proposal for hedge-fund investors to use an overlay strategy consisting of futures contracts on major asset-class indexes such as stocks, bonds, interest rates, currencies, and commodities so as to actively manage the factor exposures of their hedge-fund investments (in the interest of full disclosure, two authors of this survey—P. Lee and A. Lo—have commercial interests in an asset management company engaged in these overlay strategies). By using these "beta-blockers" in concert with properly estimated linear factor models, Healy and Lo (2009) argue that investors can reduce or eliminate exposures that they do not wish to have, while increasing exposures they feel are more rewarding, and this can be accomplished in a cost-effective manner thanks to the liquidity and capital efficiency of futures contracts and markets. Black (2006) finds that adding a small VIX position to an investment portfolio significantly reduces portfolio volatility due to the negative correlation of VIX to the S&P 500 and most hedge-fund styles. Even in cases where certain risks simply cannot be managed due to the nature of the investment, e.g., illiquidity risk in a real estate portfolio, a clear understanding of the risks will at least allow those exposed to them to prepare accordingly.

Beyond these overlay strategies, risk management is, of course, a well developed discipline with a broad and deep literature that goes well beyond hedge funds and is impossible to summarize in a single article, much less a section. However, Lo (2001) focuses on at least three unique aspects of hedge-fund risk management that are worth reviewing here. The first is the nonlinear nature of hedge-fund risk exposures, a feature that is not captured by linear factor models unless specific accommodations are made in defining the factors. A case in point is the relation between the trend-following strategies of CTAs and the S&P 500 index. A regression of the monthly returns of the CS/DJ Managed Futures Index on those of the S&P 500 Total Return Index from January 1994 through December 2014 yields the following estimated equation (standard errors in parentheses):

$$R_{\mathrm{MF},t} \;=\; \underset{(0.0021)}{0.0056} \;-\; \underset{(0.0486)}{0.0546}\, R_{\mathrm{SP500},t} \;+\; \epsilon_t \quad , \quad R^2 \;=\; 0.0050 \tag{9}$$

which shows that the Managed Futures Index has a positive and statistically significant alpha of 0.56% per month or 6.8% per year and a slightly negative and insignificant beta of -0.0546 with respect to the S&P 500. Now decompose the S&P 500 return into its positive and negative components, $R^{+}_{\mathrm{SP500},t}$ and $R^{-}_{\mathrm{SP500},t}$, where:

$$R^{+}_{\mathrm{SP500},t} \;=\; \begin{cases} R_{\mathrm{SP500},t} & if\, R_{\mathrm{SP500},t} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{10a}$$

$$R^{-}_{\mathrm{SP500},t} \;=\; \begin{cases} R_{\mathrm{SP500},t} & \text{if } R_{\mathrm{SP500},t} \le 0 \\ 0 & \text{otherwise} \end{cases} \tag{10b}$$

$$R_{\mathrm{SP500},t} \;=\; R^{+}_{\mathrm{SP500},t} \;+\; R^{-}_{\mathrm{SP500},t} \;. \tag{10c}$$

A regression of the returns of the Managed Futures Index on these two components yields the estimate:

$$R_{\mathrm{MF},t} \;=\; \underset{(0.0035)}{-0.0012} \;+\; \underset{(0.0937)}{0.1454}\, R^{+}_{\mathrm{SP500},t} \;-\; \underset{(0.0891)}{0.2411}\, R^{-}_{\mathrm{SP500},t} \;+\; \epsilon_t \quad , \quad R^2 \;=\; 0.0291 \tag{11}$$

which tells a very different story about the dynamics of the Managed Futures Index. The estimated alpha is now insignificant and negative, and the positive and negative betas are quite different, implying very different behavior in bull vs. bear markets. The beta coefficient for the positive S&P 500 returns is $+0.1454$ and statistically indistinguishable from 0, whereas the beta coefficient for the negative S&P 500 returns is -0.2411 and statistically significant at the 5% level. This asymmetry implies that when the stock market does well, the Managed Futures Index bears little relation to stocks, but when the stock market does poorly, the Managed Futures Index tends to do well, and there is little excess performance beyond these two components. In the context of the Merton (1981) timing model, this result seems to suggest that the Managed Futures Index resembles a put-plus-cash strategy. If the risk-free rate is zero, then the insignificant intercept implies that the manager can deliver this put at zero cost to investors.

Experienced investors in managed futures funds are familiar with this countercyclical pattern of trend-followers, which Kaminski (2011) describes as "crisis alpha". However, during extended periods of positive equity-market performance, trend-followers may underperform relative to their long-term average. For example, in 2012 the compound annual return of the S&P 500 was 16.0% whereas the return of the Managed Futures Index was −2.9%. These periods of underperformance can cause inexperienced investors to panic and liquidate, largely eliminating the diversification benefits of such countercyclical investments.

The second unique aspect of hedge-fund returns is tail risk. A classic example is liquidity provision among strategies that sell more liquid assets and buy less liquid assets of similar payoffs, a common feature of fixed-income arbitrage funds. Such strategies generate positive cashflows most of the time since liquid assets are priced higher than their less liquid counterparts, e.g., on-the-run vs. off-the-run U.S. Treasury securities with identical coupons, call provisions, and other terms. During normal market conditions, these strategies yield very steady returns—implying high Sharpe ratios—but during periods of market distress, they can suffer tremendous losses in the face of "flights to safety". This pattern of mostly positive small returns punctuated by the occasional large loss characterizes a number of hedge-fund strategies besides fixed-income arbitrage including equity market neutral strategies, convertible bond arbitrage, high-frequency trading, and catastrophe reinsurance.

Seasoned hedge-fund investors are fully aware of this pattern and are able to withstand periodic losses so as to capture the full benefits of these strategies. However, less experienced investors may not be as well prepared, and if they respond by reducing or liquidating their investments during periods of market distress, they will compound their losses and fail to profit from the risk premia associated with tail risk exposures.

But perhaps the biggest concern with respect to such strategies is that standard risk measures will not fully reflect their risks. Lo (2001) provides a simple illustration of a hypothetical hedge-fund strategy consisting of selling out-of-the-money put options on the S&P 500 index, which generates a very attractive risk/reward profile as long as the stock market does not decline by more than the amount that the put option is out of the money. Sharpe ratios do not reflect tail risk unless a significant loss has occurred within a given fund's track record, and when it has, the Sharpe ratio is likely to be misleadingly conservative.

This leads to the third unique aspect of hedge-fund returns which is their tendency to become highly correlated during times of market distress. To develop intuition for this aspect, consider the heat map of the empirical distribution of trailing 12-month returns of all single-manager hedge funds in the Lipper TASS database from 1997 through 2014 in Figure 5. The downward plume of density during the Financial Crisis of 2007–2009 comes in stark contrast to the relatively consistent returns of the previous years. Red and yellow indicate higher density, while turquoise and blue indicate lower density. For example, the deep red area during the mid-2000s reflects tightly-clustered performance among hedge funds, and the subsequent downward plume shows the negative skewness in crisis-period hedge fund returns. This is followed by another plume—this time upward—that reflects positive skewness in the cross-sectional distribution of post-crisis hedge fund returns as some funds profited handsomely as fears abated.

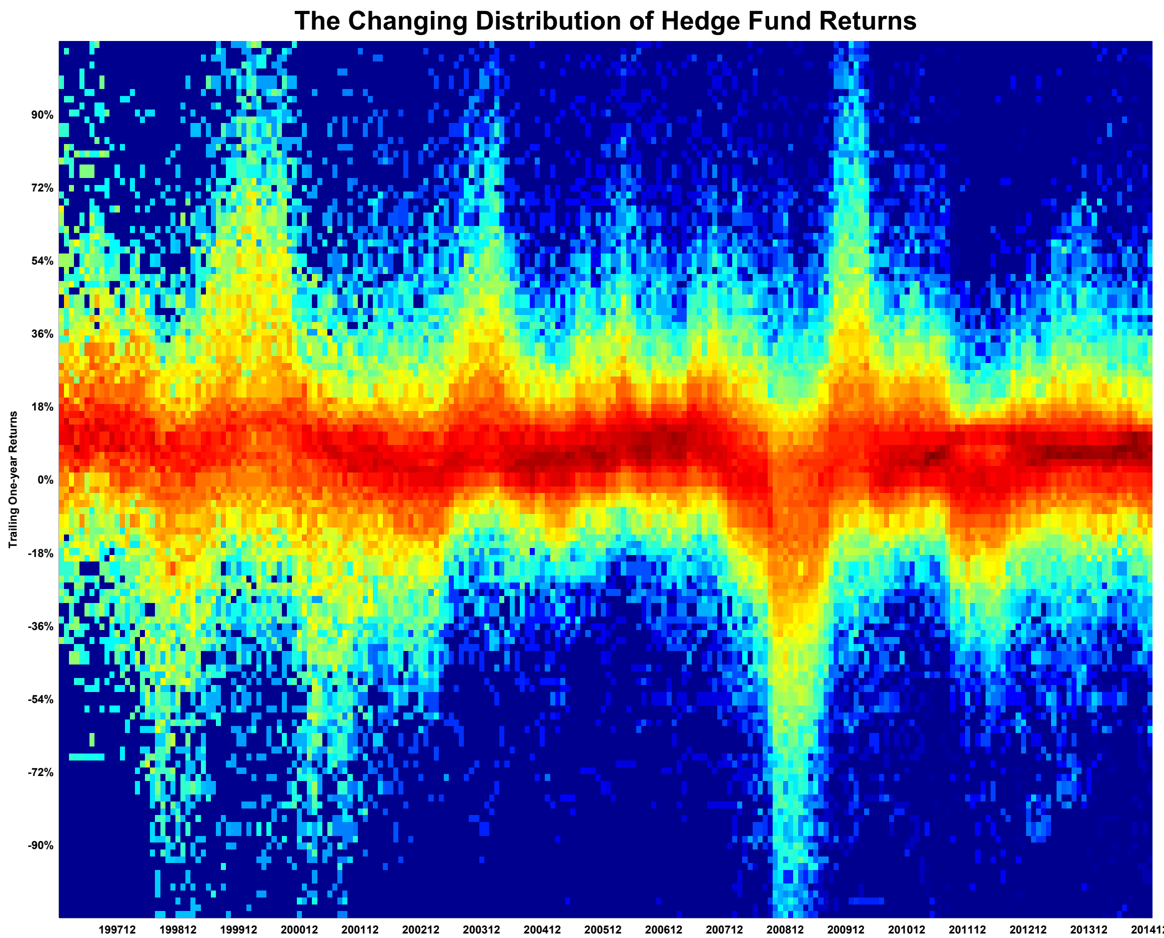


Figure 5: Empirical distribution of the trailing 12-month returns of single-manager hedge funds from 1997 through 2014, where red and yellow indicate higher density and turquoise and blue indicate lower density.

A simple way to capture this phenomenon is offered by Lo's (2001) discrete-time model of "phase-locking" behavior in which hedge fund i's returns are given by the following factor model:

$$R_{it} \;=\; \alpha_i \;+\; \beta_i\Lambda_t \;+\; I_t Z_t \;+\; \epsilon_{it} \tag{12}$$

where Λ_t, I_t, Z_t, and ϵ_{it} are mutually IID with the following moments:

$$\begin{array}{lclclcl} \mathrm{E}[\Lambda_t] & = & \mu_\lambda & , & \mathrm{Var}[\Lambda_t] & = & \sigma_\lambda^2 \\ \mathrm{E}[Z_t] & = & 0 & , & \mathrm{Var}[Z_t] & = & \sigma_z^2 \\ \mathrm{E}[\epsilon_{it}] & = & 0 & , & \mathrm{Var}[\epsilon_{it}] & = & \sigma_{\epsilon_i}^2 \end{array} \tag{13}$$

and the phase-locking event indicator I_t is defined as:

$$I_t \;=\; \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } p_0 = 1-p \end{cases} . \tag{14}$$

According to (12), expected returns are driven by three components: the fund's alpha, α_i, a "market" component, Λ_t, to which each fund has its own individual sensitivity, β_i, and a phase-locking component that is identical across all funds at all times, taking only one of two possible values: 0 (with probability p) or Z_t (with probability $1-p$).

If we assume that p is small, say 0.001, then most of the time the expected returns of fund i are determined by $\alpha_i+\beta_i\Lambda_t$, but every once in a while an additional term, Z_t, appears. If the volatility, σ_z, of Z_t is much larger than the volatilities of the market factor, Λ_t, and the idiosyncratic risk, ϵ_{it}, then the common factor, Z_t, will dominate the expected returns of all stocks when $I_t=1$, i.e., phase-locking behavior is present.

Now consider the *conditional* correlation coefficient of two funds, i and j, defined as the ratio of the conditional covariance divided by the square root of the product of the conditional variances, conditioned on $I_t=0$:

$$\mathrm{Corr}[R_{it}, R_{jt} \mid I_t = 0] \;=\; \frac{\beta_i\beta_j\sigma_\lambda^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + \sigma_{\epsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + \sigma_{\epsilon_j}^2}} \;\approx\; 0 \qquad \text{for } \beta_i \approx \beta_j \approx 0 \tag{15a}$$

where we have assumed that $\beta_i \approx \beta_j \approx 0$ to capture the market-neutral characteristic that many hedge-fund investors desire. Now consider the conditional correlation, conditioned on

$I_t = 1$:

$$\text{Corr}\big[R_{it}, R_{jt} \mid I_t = 1\big] \;=\; \frac{\beta_i\beta_j\sigma_\lambda^2 + \sigma_z^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + \sigma_z^2 + \sigma_{\epsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + \sigma_z^2 + \sigma_{\epsilon_j}^2}} \tag{16a}$$

$$\approx\; \frac{1}{\sqrt{1 + \sigma_{\epsilon_i}^2/\sigma_z^2}\sqrt{1 + \sigma_{\epsilon_j}^2/\sigma_z^2}} \quad \text{for} \quad \beta_i \approx \beta_j \approx 0 \;. \tag{16b}$$

If σ_z^2 is large relative to $\sigma_{\epsilon_i}^2$ and $\sigma_{\epsilon_j}^2$, i.e., if the variability of the market-distress component dominates the variability of the residuals of both funds—a plausible condition that follows from the very definition of market distress—then (16) will be approximately equal to 1! When phase-locking occurs, the correlation between funds i and j—close to 0 during normal times—can become arbitrarily close to 1.

But the most dangerous feature of (12) is the fact that it implies a very small value for the *unconditional* correlation, which is the quantity most readily estimated and most commonly used in risk reports, VaR calculations, and portfolio decisions. To see why, recall that the unconditional correlation coefficient is simply the unconditional covariance divided by the product of the square roots of the unconditional variances, hence the unconditional correlation coefficient under (12) is given by:

$$\text{Corr}[R_{it}, R_{jt}] \;=\; \frac{\beta_i\beta_j\sigma_\lambda^2 + p\sigma_z^2}{\sqrt{\beta_i^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\epsilon_i}^2}\sqrt{\beta_j^2\sigma_\lambda^2 + p\sigma_z^2 + \sigma_{\epsilon_j}^2}} \tag{17a}$$

$$\approx\; \frac{p}{\sqrt{p + \sigma_{\epsilon_i}^2/\sigma_z^2}\sqrt{p + \sigma_{\epsilon_j}^2/\sigma_z^2}} \qquad \text{for } \beta_i \approx \beta_j \approx 0 \;. \tag{17b}$$

If we let $p = 0.001$ and assume that the variability of the phase-locking component is 10 times the variability of the residuals, ϵ_i and ϵ_j, this implies an unconditional correlation of:

$$\text{Corr}[R_{it}, R_{jt}] \;\approx\; \frac{p}{\sqrt{p + 0.1}\sqrt{p + 0.1}} \;=\; 0.001/.101 \;=\; 0.0099$$

or less than 1%. As the variance, σ_z^2, of the phase-locking component increases, the unconditional correlation (17) also increases so that eventually, the existence of Z_t will have an impact. However, to achieve an unconditional correlation coefficient of, say, 10%, σ_z^2 would have to be about 100 times larger than σ_ϵ^2. Without the benefit of an explicit risk model such as (12), it is virtually impossible to detect the existence of a phase-locking component from standard correlation coefficients.

These considerations suggest that risk management for hedge funds cannot be approached in the same manner as for traditional investments. Measuring and managing the risk exposures of hedge funds require not only more sophisticated risk analytics, but also a deeper understanding of the nature of the strategies being managed.

6.6 Hedge-Fund Beta Replication

Our discussion of factor modeling suggests that a portion of hedge funds' returns may be attributable to simple investments that do not require hedge funds' high fees or expensive trading infrastructure. In recent years the insights of a handful of researchers encouraged asset managers to develop strategies that generate the "simple" portion of funds' returns while charging low fees and providing greater transparency and liquidity. Today billions of dollars are managed in these strategies. In the interest of full disclosure, two of the authors of this article—P. Lee and A. Lo—are affiliated with an asset management company offering a hedge-fund beta replication mutual fund. While every effort has been undertaken to avoid bias, readers should be aware of this potential conflict of interest and interpret the discussion in this section accordingly.

Current replication methods fall into three categories: linear factor model replication, replication of strategies, and replication of payoff functions or return distributions. In the linear factor model approach, a linear factor model with investable factors is used to construct a portfolio with the same betas—and corresponding risk premia—of the aggregate hedge-fund industry or sector being replicated. Successful linear factor model replication depends on the explanatory power of the factors and the timeliness of the beta estimates. In the strategy replication approach, a manager employs a rules-based strategy that aims to make the same sort of trades that a hedge fund would make and thereby generate similar returns. One challenge this approach faces is that a fund that trades in a manner similar to a hedge fund may effectively become a hedge fund itself, and not a replicator at all. Finally, the distributional approach aims to replicate characteristics of the probability distribution of hedge-fund returns. The challenge with this approach is that matching payoff distributions can sometimes be more complex and costly than implementing the hedge-fund strategy itself.

Given the many linear factor models that have been estimated with hedge fund returns (see Section 6.2), a natural starting point for hedge-fund beta replication is to use these models to construct portfolios with alternative beta exposures. This is the approach proposed by Hasanhodzic and Lo (2006, 2007), who constructed "linear clones" of individual hedge funds in the Lipper TASS hedge fund database using six factors: the U.S. Dollar Index return, the return on the Lehman Corporate AA intermediate Bond Index, the spread between the Lehman BAA Corporate Bond Index and the Lehman Treasury Index, the S&P 500 total returns, the Goldman Sachs Commodity Index total return, and the first-difference of the end-of-month value of the VIX.

Based on these findings, they proposed using liquid futures contracts to construct replication portfolios. This proposal was subsequently implemented by the investment advisory firm AlphaSimplex Group, LLC in 2008 using just over two dozen futures contracts; the resulting strategy is currently the largest hedge-fund beta replication mutual fund (see Lee and Lo (2014) for further discussion). However, Goldman Sachs was the first to market with a hedge-fund beta replication mutual fund designed to track the Goldman Sachs Absolute Return Tracker Index. Other large banks and some asset managers have followed suit with their own versions of hedge-fund beta replication indexes or funds, including Barclays, Credit Suisse, Deutsche Bank, Index IQ, Merrill Lynch, and Société Générale.

Amenc, Martellini, Meyfredi, and Ziemann (2010) extend Hasanhodzic and Lo (2007) by assessing the out-of-sample performance of various nonlinear and conditional hedge fund replication models. They find that going beyond the linear case does not necessarily enhance replication power, but selecting factors via economic analysis yields substantial improvement in out-of-sample replication quality, irrespective of the underlying form of the factor model. Overall, the authors confirm the findings in Hasanhodzic and Lo (2007) that the performance of replicating strategies is systematically inferior to that of the actual hedge funds, but still attractive enough to warrant consideration by investors seeking additional sources of risk premia.

With respect to the replication of hedge-fund payoff distributions, Kat and Palaro (2005, 2006a,b) argue that sophisticated dynamic trading strategies involving liquid futures contracts can replicate many of the statistical properties of hedge-fund returns. The authors propose several models for the replication of return distribution. More generally, Bertsimas, Kogan, and Lo (2001) have shown that securities with very general payoff functions (like hedge funds, or complex derivatives) can be synthetically replicated to an arbitrary degree of accuracy by dynamic trading strategies—called "epsilon-arbitrage" strategies—involving more liquid instruments. Although these algorithmic strategies can replicate virtually any payoff distribution, the complexity of the strategies make this form of replication less attractive to investors that do not have the necessary trading and risk management infrastructure.

A less complex approach to hedge-fund beta replication is to implement "plain vanilla" versions of certain hedge-fund strategies, specifically those that can be fully described by mechanical trading rules. Examples include the currency carry-trade strategy, trend-following managed futures, risk arbitrage, and a 130/30 long/short equity strategy.[23] Investment products based on these algorithms acknowledge that no manager alpha is contained in their funds; instead, they seek to provide the corresponding risk premia associated with these strategies at lower cost and with greater liquidity than their hedge-fund counterparts.

Kazemi, Li, and Tu (2008) develop a replication methodology suited for hedge fund performance evaluation. The methodology develops two replicating portfolios such that the distribution properties of the target are matched. The first portfolio delivers the statistical properties at the lowest possible cost while the other is more expensive but delivers the same properties as the target. Azlen (2011) combines a core holding of single managers and a secondary holding of a blend of synthetic replication products to reduce costs and increase liquidity.

Using Bayesian filters, Roncalli and Weisang (2010) propose solutions for a tracking problem in hedge fund replication. They find that hedge fund trackers have smaller Sharpe ratios than their respective indexes, even though they generally exhibit lower volatilities. The trackers also exhibit a smaller maximum drawdown and kurtosis of the returns. Many illiquid strategies (e.g., distressed securities), strategies with small betas (e.g., relative value), and strategies based on stock picking (e.g., merger arbitrage and equity market neutral) present low correlation with their respective trackers, and thus are hard to replicate. Interestingly, for funds of funds the authors find that a replicating portfolio does not have a high correlation with its respective index, but still exhibits similar performance.

Finally, Tuchschmid, Wallerstein, and Zaker (2010) survey 21 replication funds and indexes from April 2008 to May 2009. They find that these replication products are sold at a far lower fee level than hedge funds, and that many of them seem to live up to their promise of low correlation with market indexes. All of them underperformed during the Financial Crisis of 2007–2009, but so did hedge funds over this period. As a result, the authors conclude that, benchmarked against hedge-fund indexes, many replication products perform well.

7 The Financial Crisis

No review of the hedge fund literature would be complete without some discussion of the impact of the Financial Crisis of 2007–2009 on the hedge-fund industry as well as the industry's role in the crisis, issues that are both nuanced and important from all stakeholders'

[23] A number of carry-trade and trend-following managed futures mutual funds and ETFs already exist. See Mitchell and Pulvino (2001) for a mechanical risk-arbitrage strategy, and Lo and Patel (2008) and Hasanhodzic, Lo, and Patel (2009) for a mechanical 130/30 long/short equity strategy.

perspectives. If hedge funds are the "tip of the spear" in exploiting profitable opportunities during good times, they are also the "canary in the coal mine" that suffers first during bad times.

Figure 5 shows that the recent crisis has had an unprecedented effect on the industry. While some funds were able to profit handsomely from these adverse market conditions, about 70% of the funds in our sample experienced negative returns in 2008. Losses suffered by funds invested in illiquid assets such as credit were particularly disproportionate to those funds' typical volatility levels. As the crisis began, reports of "10-sigma" or "20-sigma" events were commonplace until a sort of ennui set in, and it became understood that models designed to characterize the behavior of asset prices during normal market conditions had little relevance in a crisis so extreme that the need to survive trumped many financial institutions' normal profit-seeking behaviors.

In the face of heavy losses and investor redemptions, a record number of funds shut down, and for the first time in the industry's modern history the number of funds began to decline (see Table 3). Moreover, these losses led many investors to re-evaluate the significance of supposedly well-understood concepts such as diversification and absolute return strategies. Hedge fund managers rushing to exit from crowded trades found that once-diversifying positions were now highly correlated, and many suffered acute losses. However, in a recent study, Reca, Sias, and Turtle (2013) find that hedge fund trades are not very crowded, subject to the limitations of 13F data. Managers whose portfolios survived the mayhem were often more agile, more liquid, more tactical, and more contrarian, e.g., Managed Futures, Global Macro, Dedicated Short Bias funds, and funds with less autocorrelated returns.

Although many hedge funds were unsuspecting victims of the Financial Crisis of 2007–2009, several studies have considered the possibility that hedge funds played a significant role in causing the crisis. Ever since the demise of LTCM in 1998, hedge funds have become inextricably linked to systemic risk, though the links are still not yet well defined. A 2011 survey conducted by the Financial Crisis Inquiry Commission (FCIC) of more than 170 hedge funds encompassing over $1.1 trillion in assets as of early 2010 found that hedge funds were one of the largest purchasers of the riskiest equity tranches of collateralized debt obligation (CDO) securities. More than half of the equity tranches were purchased by hedge funds that simultaneously shorted other tranches, thus engaging in a correlation trade. However, many hedge funds also used credit default swaps (CDSs) to take offsetting positions in different tranches of the same CDO security. Therefore, hedge funds would profit if the CDOs performed, but stood to earn even more if the entire market crashed (FCIC (2011)). By being positioned to benefit from financial instability, hedge funds had an incentive to increase systemic risk.

The crisis underscored the need for regulators to obtain greater transparency from hedge funds so as to gauge the potential systemic risks posed by certain strategies such as the correlation trade, to keep track of crowded trades (which could be vulnerable to runs such as the August 2007 Quant Meltdown and the more opaque runs on mortgage-linked products), to evaluate liquidity risks, etc. In 2012, the SEC began collecting confidential hedge-fund data via Form PF. Regulators now have access to limited aggregate results about hedge-fund positions, exposures, leverage, the use of derivatives, and different types of risks (SEC (2013) and OFR (2013)).

Moreover, because hedge funds do lie outside the purview of banking supervision despite the fact that they now engage in many of the same businesses as banks, they could pose unique risks to financial stability that are more difficult to measure and manage in the current regulatory framework. Although several industry leaders have argued that the hedge-fund industry is simply not large enough to have an impact on financial stability, the experience of LTCM—a hedge fund with only $4.7 billion in assets just prior to August 1998—seems to suggest otherwise. But even if the hedge-fund industry played only a supporting role in the most recent crisis, as the empirical evidence suggests, its unconstrained and dynamic investment strategies can certainly facilitate both the build-up of systemic risk during periods of market exuberance and the propagation of systemic shocks during periods of market dislocation.

In fact, contributions to systemic risk may be an unavoidable consequence of the provision of market liquidity and price discovery during normal market conditions. Although often criticized as being part of the opaque "shadow banking system", hedge funds also played a critical role in supporting the economy when the official banking system ground to a halt in 2007–2009. For example, of the eight investment funds created jointly by the private sector and the U.S. Treasury as part of its Public-Private Investment Program (PPIP) to purchase "troubled assets", i.e., mortgage-backed securities, from banks so as to allow them to start lending again, two were co-sponsored by hedge funds (Angelo, Gordon & Co. and Oaktree),[24] and many of the investors in all eight funds were hedge-fund investors. Hedge funds and their investors are central to the financial ecosystem in providing much-needed capital, particularly during times when typical investors are fleeing to safety.

Whether it is possible to keep the benefits that hedge funds offer while eliminating the potential risks they pose is still an open question. But even if this is not possible, monitoring the hedge-fund industry is essential for developing an accurate map of risk-taking activity

[24]Incidentally, these two funds earned the highest net internal rates of return for their investors among the eight: 26.3% for the Oaktree PPIP Fund, L.P. and 24.8% for the AG GECC PPIF Master Fund, L.P. from inception to end (U.S. Treasury, 2013).

in the economy, and may also yield early warning signs of impending financial distress. This latter objective is the focus of Section 7.1 which contains a summary of the literature on early indications of the Financial Crisis of 2007–2009 among a subset of hedge funds. We then turn to a more systematic accounting of the hedge-fund winners and losers during the crisis period in Section 7.2, and summarize the post-crisis performance of hedge funds in Section 7.3. Finally, in Section 7.4 we review the subset of the burgeoning systemic risk literature that involves the hedge-fund industry.

7.1 Early Warning Signs of the Crisis

Most of the public first became aware of the recent financial crisis during the fourth quarter of 2008 when Lehman Brothers filed for bankruptcy and the Reserve Primary Fund "broke the buck". However, well before 2008, early warning signs of the crisis emerged in three distinct but interrelated sectors—U.S. residential real estate, banking, and hedge funds—and were highlighted by several academics. In January 2005, Shiller (2005) published excerpts from his new edition of *Irrational Exuberance* in *Money Magazine* in which he warned of an asset bubble in the U.S. housing market. In August 2005, Rajan (2005) presented research showing that recent financial innovations had increased risk in the banking sector. And at an October 2004 conference organized by the National Bureau of Economic Research on systemic risk, Chan, Getmansky, Haas, and Lo (2004) first presented their empirical findings of an increased probability of a systemic shock in the hedge-fund industry due to significant losses among large, leveraged, hedge funds investing in illiquid securities (see, also, their published versions, Chan, Getmansky, Haas, and Lo (2006, 2007)).

Chan, Getmansky, Haas, and Lo (2004) based their inferences on several indirect measures including: asset-weighted return autocorrelations that pointed to greater reliance on illiquid assets (see Section 5); regime-switching models that pointed to lower expected returns, higher volatility, and, therefore, greater use of leverage; and increasing common-factor exposures in individual hedge-fund returns, implying higher conditional correlations when market indexes crash (see Section 6). In September 2005, the *New York Times* published a story about this research and concluded that "The nightmare script ... would be a series of collapses of highly leveraged hedge funds that bring down the major banks or brokerage firms that lend to them" (Gimein (2005)). Such an outcome seemed absurd at the time, but the losses that brought down Bear Stearns—a company founded in 1923 with assets of $350 billion, over 13,500 employees, and record net revenues of $9.2 billion in 2006—began with their two subprime mortgage hedge funds: the Bear Stearns High-Grade Structured Credit Fund and the Bear Stearns High-Grade Structured Credit Enhanced Leveraged Fund.

With the benefit of hindsight, these three different warning signs, generated by three very different sources, were manifestations of the very same forces at play in the economy. Real estate prices were being driven to unprecedented levels by tremendous inflows of assets from around the world via both the banking system and capital markets, thanks to financial innovations such as securitization and the CDS. And because hedge funds are largely unconstrained in their investment mandates and trading style, stress fractures in the financial system are more likely to show up first in the hedge-fund industry. Their aggressive risk appetite and incentive to generate absolute return cause them to be first to take advantage of emerging investment opportunities, and also the first to take losses when crisis hits. In fact, signs of credit problems were visible in the hedge-fund industry as early as May 2005 when convertible arbitrage funds suffered extraordinary losses in the aftermath of the downgrading of General Motors and Ford corporate debt to "non-investment-grade" status by the rating agencies. The two automakers had over $450 billion of debt outstanding, all of which turned to junk bonds overnight.

These downgrades were emblematic of a broader deterioration of credit quality throughout debt markets, wreaking havoc with highly leveraged financial institutions and many of their counterparties. Like a flu pandemic in the age of international air travel, the credit crisis spread quickly around the globe, occasionally erupting in unexpected venues. One of the most unexpected venues was a little-known corner of the hedge-fund industry called equity market neutral or "statistical arbitrage" funds. During the first four days of the second week of August 2007, these highly quantitative equity trading funds all experienced significant losses at the same time, for no apparent reason, and then on the last day of that week, they experienced dramatic reversals. The press dubbed this episode the "Quant Meltdown of August 2007" but offered no explanation for what had happened—hedge funds do not talk to the press.

In attempt to piece together this puzzling sequence of events, Khandani and Lo (2007) combined inferences from Lipper TASS hedge-fund data and simulations of a specific equity market neutral trading strategy using historical stock returns from January 1995 through September 2007 and reproduced the huge losses in August 2007. From these simulations, they developed a hypothetical narrative to explain the Quant Meltdown: the losses were initiated by the rapid "unwind" of one or more sizable quantitative equity market-neutral portfolios, likely a forced liquidation stemming from a margin call or a desire to cut risk, given the speed and price impact with which this unwind occurred. These initial losses then put pressure on other equity market neutral funds which, by definition, are engaged in similar strategies and, therefore, hold similar portfolios,[25] causing further losses by triggering stop/loss and deleveraging policies. This is one of the clearest examples of Brunnermeier's (2009) margin and deleveraging spirals.[26] Adrian and Shin (2008, 2010) document a pro-cyclical relationship between the leverage of U.S. investment banks and the sizes of their balance sheets and explore the aggregate effects that such a relationship can have on asset prices and the volatility risk premium. This empirical observation increases the likelihood of Brunnermeier's (2009) margin and deleveraging spiral. Allen and Carletti (2008) provide a more detailed analysis of the role of liquidity in the financial crisis and consider the source of the current "cash-in-the-market" pricing, i.e., market prices that are significantly below what plausible fundamentals would suggest.

A significant rebound of these strategies occurred on August 10th, presumably in response to an announced injection of capital into one of the hardest-hit funds, Goldman Sachs's Global Equity Opportunities Fund. But another factor that may have contributed to the reversal on the 10th was the overnight liquidity injection by the major central banks into short-term interbank lending markets in response to the so-called "run on repo" on August 9th (see Gorton and Metrick (2012)).

The research departments of the major investment banks also produced analyses, e.g., Goldman Sachs Asset Management (2007) and Rothman (2007a,b,c), citing coordinated losses among portfolios constructed according to several well-known quant factors, and arguing that simultaneous deleveraging and a lack of liquidity were responsible for these losses. For example, the study by Rothman (2007a), which was first released on August 9, 2007, reports the performance of a number of quant factors and attributes the simultaneous bad performance to "a liquidity based deleveraging phenomena". Goldman Sachs Asset Management (2007) provides additional evidence from foreign equity markets (Japan, U.K., and Europe-ex-U.K.), indicating that the unwinds involved more than just U.S. securities. In a follow-up study, Rothman (2007b) called attention to the perils of endogenous risk; in referring to the breakdown of the risk models during that period, he concluded that: "By and large, they understated the risks as they were not calibrated for quant managers/models

[25] In particular, Khandani and Lo (2011a) simulate simple equity market neutral strategies using five factors commonly used in quantitative equity trading strategies—three value-factors similar to those in Lakonishok, Shleifer, and Vishny (1994), and two momentum factors as in Chan, Jegadeesh, and Lakonishok (1996)—and show that funds began unwinding portfolios constructed with these factors as early as the beginning of July 2007.

[26] Although Brunnermeier's (2009) focus was on mortgage-related losses, his argument applies verbatim to the Quant Meltdown. In both cases, the amplification mechanism is key: borrowers' deteriorating balance sheets generate liquidity spirals from relatively small shocks, and once started, these spirals continue as lower asset prices and higher volatility raise margin levels and lower available leverage.

becoming our own asset class, creating our own contagion".[27] And, most recently, Litterman (2013) provides a fascinating personal account of these events as he witnessed them firsthand as a partner at Goldman Sachs during August 2007.[28] His analysis of the Quant Meltdown is both riveting and intellectually stimulating, and should be required viewing for all hedge-fund managers, investors, and financial regulators.

In its conclusion, the Goldman Sachs Asset Management (2007) study suggests that "...it is not clear that there were any obvious early warning signs... No one, however, could possibly have forecasted the extent of deleveraging or the magnitude of last week's factor returns". Using transactions data from July through September 2007, Khandani and Lo (2011a) show that the dislocation was exacerbated by the withdrawal of market making risk capital—possibly by high-frequency hedge funds—starting on August 8. This highlights the endogenous nature of liquidity risk and the degree of interdependence among market participants, or "species" in the terminology of Farmer and Lo (1999). The fact that the ultimate origins of this dislocation were apparently outside the equity market neutral sector—most likely in a completely unrelated set of markets and instruments—suggests that the financial system is much more highly interconnected and tightly coupled than previously recognized.

7.2 Winners and Losers

During periods of financial distress, hedge funds have often suffered larger losses than traditional risk-assessment methods have predicted. A number of authors have investigated this curious phenomenon and have pointed to the potential impact of latent factors (see Section 6), with illiquidity being the most significant. The prices of illiquid assets often plummet during market dislocations in response to forced liquidations that result in fire-sales, generating losses for all entities invested in illiquid assets. As can be seen in Figure 6, funds with the highest autocorrelated returns—an indication of illiquidity (see Section 5.1)—underperform during periods of market stress. More directly, Billio, Getmansky, and Pelizzon (2013) estimate the latent factor present in hedge fund returns during the 1998 and 2007–2009 financial crises, and find that this factor is connected to funding and asset liquidity. Cao, Liang, Lo, and Petrasek (2014) conclude that hedge fund trading increases market efficiency in general. However, during crises, hedge funds face leverage-induced margin calls and liquidity squeezes hence their trading leads to greater price deviations from fundamentals during these episodes. Therefore, the positive role of hedge funds in improving market efficiency critically

[27] See also Montier (2007).

[28] See http://techtv.mit.edu/collections/mitsloanfinance/videos/25938-s-donald-sussman-award-lecture-the-quant-liquidity-crunch-of-2007-an-unrecognized-crowded-trade

depends on funding liquidity. Figure 6 highlights three crises: the Russian debt default and LTCM's collapse (1998), the automakers' bond downgrade (2005), and the recent financial crisis (2007–2009). During each of these periods of stress, highly autocorrelated funds underperformed their more liquid peers. In "normal" years, however, illiquid funds generally appear to be the outperformers (Aragon (2007) and Sadka (2010, 2012)). In fact, less liquid funds outperformed others in 2009, perhaps driven by a rebound in the prices of illiquid assets.

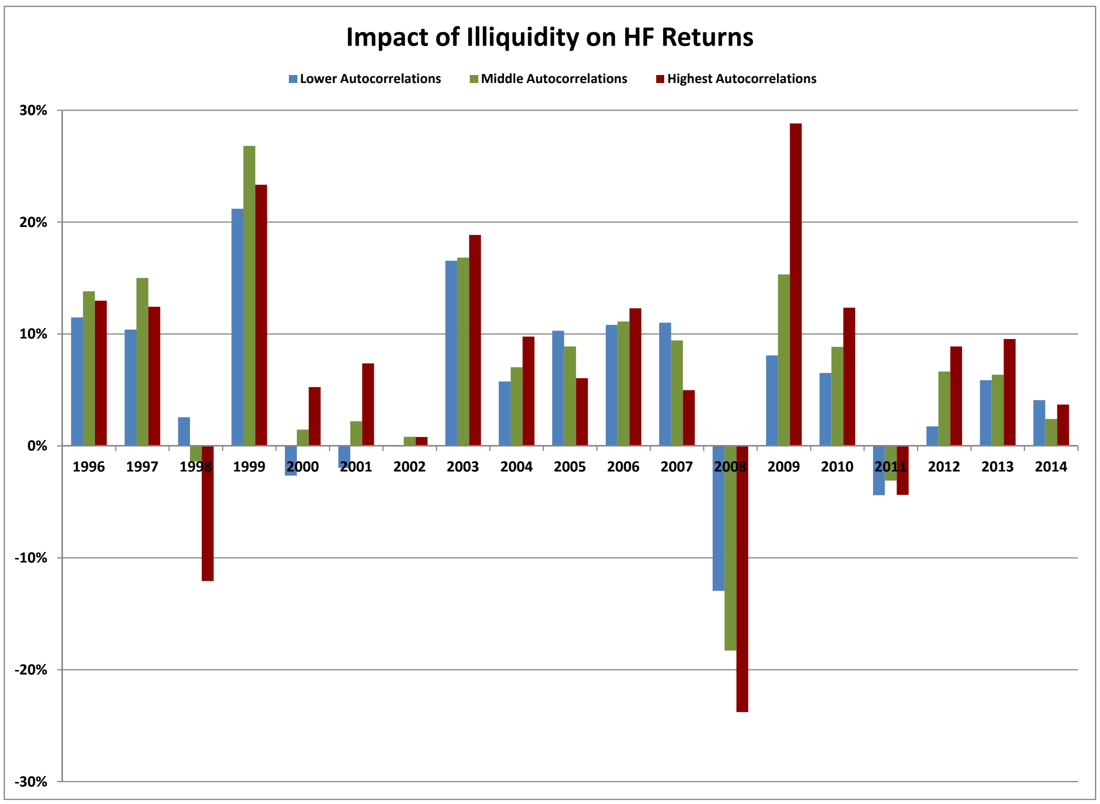


Figure 6: Average hedge-fund performance for individual hedge funds in three liquidity groups from the Lipper TASS database: the most liquid (lowest autocorrelation), medium-liquid (medium autocorrelation), and the least liquid (highest autocorrelation). Returns are calculated yearly for each liquidity group from January 1996 through December 2014.

In 2008 the Financial Crisis was at its most intense, though equity markets continued to decline until mid-March of 2009. Although hedge funds earned positive returns in 2007 and 2009 on average, the combination of plunging equity markets and evaporating liquidity in 2008 proved toxic and, in many cases fatal, leading to the industry's worst-ever annual return and the shutdown of over 2,000 hedge funds, as documented in Table 3. In 2008, the attrition rate was 21%, the average hedge fund return was −18.4%, and the proportion of hedge fund managers reporting negative returns for the year was 71%. Critics of the industry asked why these absolute-return funds failed to generate positive returns, while supporters noted that an investor would have fared far better in the average hedge fund than in, for example, a stock index fund.

Lehman Brothers acted as one of the major prime brokers to the hedge-fund industry prior to its bankruptcy on September 15, 2008. Aragon and Strahan (2012) study an example of the propagation of illiquidity during the financial crisis: Lehman and the hedge funds that used it as a prime broker. They document that the failure rate of Lehman's hedge-fund clients doubled after the bankruptcy, relative to funds with similar performance characteristics using other brokers. The authors also show that stocks held by Lehman's hedge-fund clients prior to the bankruptcy experienced unexpectedly large declines in liquidity after the bankruptcy. Ben-David, Franzoni, and Moussawi (2012) show that in 2008Q3–Q4, hedge funds sold about 29% of their aggregate portfolio. Redemptions and margin calls were the primary drivers of the selloffs. In comparison, fund outflows and stock sales for mutual funds were not as severe.

The remainder of 2009 was marked by the sharp appreciation of depressed asset prices as governments flooded the markets with liquidity. 2010 saw a continued, albeit uneven, recovery and the development of the European sovereign debt crisis. Hedge fund attrition, though still in double digits, decreased to 15% in 2009 and 2010, and average hedge-fund returns were positive in both years. Although hedge funds in most categories experienced losses during 2008, those in three categories did not (see Table 12). As one would expect in a declining equity market, Dedicated Short Bias produced handsome returns. Managed Futures, an investment style that makes heavy use of trend-following, also performed well. Indeed, one of the primary motivations for investing in managed futures funds is their performance during and after crises, i.e., Kaminski's (2011) crisis alpha. However, Global Macro—the more-discretionary counterpart to Managed Futures that does not have as much crisis alpha—finished the year roughly flat. Table 13 shows that funds belonging to these three categories exhibited the lowest autocorrelation and lowest correlation with the S&P 500 during this period, which supports the narrative that the evaporation of liquidity and the decline in the prices of equities or equity-like investments played an important role in hedge funds' losses.

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity Hedge	Managed Futures	Multi-Strategy
2004	1.2%	-9.8%	16.8%	3.9%	12.3%	5.5%	2.6%	8.5%	2.5%	4.5%
2005	-1.7%	-0.2%	21.5%	5.2%	8.0%	4.3%	7.6%	10.7%	4.0%	8.1%
2006	11.9%	-13.2%	23.2%	6.7%	13.8%	7.1%	5.0%	12.1%	8.5%	8.7%
2007	2.0%	3.7%	22.3%	5.7%	6.5%	-0.3%	10.5%	8.5%	10.3%	7.3%
2008	-32.2%	31.2%	-38.2%	-12.9%	-23.2%	-18.7%	0.8%	-20.8%	19.6%	-21.1%
2009	43.8%	-17.1%	34.7%	6.7%	24.7%	20.3%	11.3%	19.0%	-5.9%	9.4%
2010	12.7%	-3.0%	11.2%	4.3%	10.4%	5.0%	6.2%	9.4%	12.4%	6.3%
2011	-7.1%	5.1%	-14.3%	-0.6%	-2.6%	5.1%	1.1%	-7.5%	-4.8%	2.2%
2012	11.0%	-13.7%	5.8%	4.1%	9.4%	7.4%	5.8%	7.1%	-3.4%	7.7%
2013	1.7%	-0.4%	2.7%	7.6%	11.2%	4.6%	3.1%	14.5%	-1.5%	5.8%
2014	-2.0%	6.0%	-1.6%	4.5%	-2.3%	3.3%	2.5%	1.3%	12.7%	4.1%

Table 12: Average annual returns of Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy funds from January 2004 through December 2014. The highest average returns are color-coded in shades of blue, intermediate values are yellow, and the worst values are red and orange.

From 2004 to 2014	# fund-months	Annualized Mean	Annualized Volatility	Sharpe Ratio	Sortino Ratio	Skewness	Kurtosis	Maximum DD	S&P 500 Correl.	ac(1)	Box-Q(3) p-value
Convertible Arbitrage	10133	2.3%	8.8%	0.09	0.12	-3.08	23.06	-34.4%	0.60	0.48	0.00
Dedicated Short Bias	1648	-1.8%	10.1%	-0.32	-0.56	0.41	3.12	-34.1%	-0.71	0.16	0.27
Emerging Markets	39670	5.6%	11.2%	0.36	0.55	-1.17	6.62	-40.6%	0.73	0.36	0.00
Equity Market Neutral	22129	3.0%	3.2%	0.49	0.66	-2.20	10.50	-14.6%	0.63	0.45	0.00
Event Driven	30113	5.5%	6.0%	0.66	1.00	-1.40	6.90	-24.8%	0.76	0.48	0.00
Fixed Income Arbitrage	15191	3.6%	4.5%	0.47	0.55	-5.16	41.74	-20.7%	0.57	0.32	0.00
Global Macro	27845	5.1%	3.7%	0.96	1.94	0.21	3.85	-4.7%	0.45	0.00	1.00
Long/Short Equity Hedge	144706	5.1%	7.2%	0.50	0.81	-0.82	4.23	-24.7%	0.82	0.26	0.00
Managed Futures	39056	4.6%	8.8%	0.36	0.70	0.28	3.22	-14.5%	0.07	0.02	0.33
Multi-Strategy	72889	3.5%	4.6%	0.45	0.62	-1.95	10.19	-21.5%	0.68	0.44	0.00
Fund of Funds	247483	2.1%	5.0%	0.13	0.18	-1.36	6.66	-21.9%	0.66	0.35	0.00
All Single Manager Funds	425222	4.7%	5.6%	0.57	0.89	-1.05	5.86	-20.5%	0.77	0.32	0.00

Table 13: Summary statistics for the returns of the average fund in each Lipper TASS style category from January 2004 through December 2014. Number of fund months, annualized mean, annualized volatility, Sharpe ratio, Sortino ratio, skewness, kurtosis, maximum drawdown, correlation coefficient with the S&P 500, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags for the 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database are reported. Sharpe and Sortino ratios are adjusted for the three-month U.S. Treasury Bill rate. The "All Single Manager Funds" category includes the funds in all 10 main Lipper TASS categories and any other single-manager funds present in the database (relatively few) while excluding funds of funds.

7.3 Post-Crisis Performance

In the years following the financial crisis, some industry analysts have expressed disappointment with hedge funds in light of their underperformance relative to public equities. As a result, investors' ever-present interest in gauging manager alpha has a new and urgent form: in the post-crisis era, have hedge funds lost their ability to generate attractive returns? Although it is still too soon to answer this question with any degree of empirical accuracy, some preliminary facts suggest a possible response.

In Table 14 we report summary statistics for the returns of the average hedge fund during pre- and post-crisis periods, where the pre-crisis period is from January 1996 through December 2006 and the post-crisis period is from January 2010 through December 2014. In each period, we calculate the bias-adjusted average monthly returns for single-fund managers in the Lipper TASS database, along with the other standard measures of investment performance. The entries confirm the popular perception that the absolute returns of hedge funds were higher on average during the pre-crisis period: 8.7% pre-crisis vs. 4.2% post-crisis. Moreover, this inequality holds for every single category.

However, Table 14 also shows that, in the post-crisis period, the Sharpe ratios of hedge funds have been as high as they were in the pre-crisis period or higher, suggesting that managers are no less skilled at generating returns now than they were before the crisis. Specifically, across all categories, the average Sharpe ratio is 0.72 in the pre-crisis period and 1.00 in the post-crisis period. As a check, we calculated the Sharpe ratio of the CS/DJ Hedge-Fund Index for the same periods, and again we found that the Sharpe ratio had, if anything, increased: 0.97 in the pre-crisis period and 1.29 in the post-crisis period. This result is hardly definitive, as the length of the post-crisis period is still rather short and many authors have proposed more-elaborate measures of hedge fund skill. Nonetheless, it suggests that any reports of the disappearance of hedge fund manager skill may be quite exaggerated.

This surprising result suggests a somewhat different narrative regarding the source of hedge-fund underperformance. The most obvious explanation is the fact that the average volatility of hedge funds' returns was lower in the post-crisis period, damping absolute returns even as risk-adjusted returns remained strong. We estimate that the annualized volatility of the cross-sectionally averaged hedge fund returns in the Lipper TASS database dropped from 6.5% to 4.2% between the two periods, and among the individual categories, only Convertible Arbitrage funds have higher average volatilities in the post-crisis period. This decline in volatility is likely due to lower amounts of leverage being deployed in the hedge-fund industry for several reasons: a decrease in risk appetite among investors in the aftermath of the financial crisis, more stringent capital requirements on the part of regulators, and fewer

Category	# Fund-Months	Ann. Mean (%)	Ann. SD (%)	Sharpe Ratio	Sortino Ratio	Skew.	Kurt.	MaxDD (%)	Corr. to S&P 500 (%)	ρ_1 (%)	Box-Q(3) p-value (%)
January 1996 to December 2006											
Convertible Arbitrage	7,827	8.1	4.3	0.95	1.53	-1.25	8.63	-8.70	42.9	45.9	0.0
Dedicated Short Bias	1,384	-2.3	18.8	-0.31	-0.58	0.59	4.17	-42.29	-76.8	8.9	19.1
Emerging Markets	12,673	11.6	15.7	0.47	0.69	-1.61	10.51	-49.26	58.5	28.0	0.8
Equity Market Neutral	11,537	6.5	3.0	0.82	1.82	2.05	16.06	-2.21	3.0	-11.7	22.4
Event Driven	18,565	9.4	5.2	1.02	1.55	-2.02	13.89	-12.56	54.7	32.3	0.2
Fixed Income Arbitrage	7,749	6.8	3.7	0.75	0.95	-3.56	24.53	-13.69	-1.0	42.7	0.0
Global Macro	8,948	4.7	6.1	0.14	0.26	0.46	4.17	-14.24	21.7	2.5	41.6
Long/Short Equity Hedge	69,160	11.1	9.8	0.71	1.33	0.15	5.31	-18.52	68.8	18.7	16.7
Managed Futures	13,761	5.0	9.8	0.11	0.20	0.14	2.97	-16.34	-8.7	0.0	72.9
Multi-Strategy	8,100	8.5	5.2	0.85	1.43	-0.73	5.16	-6.67	49.1	0.1	65.1
Fund of Funds	55,507	6.6	6.4	0.41	0.68	-0.33	6.51	-12.97	53.3	22.2	5.0
All Single Manager Funds	163,702	8.7	6.5	0.72	1.28	-0.26	5.46	-10.95	65.2	19.2	13.1
January 2010 to December 2014											
Convertible Arbitrage	3,940	3.0	5.7	0.52	0.96	-0.07	2.67	-10.20	50.4	10.6	63.6
Dedicated Short Bias	571	-1.5	7.3	-0.21	-0.33	-0.40	2.94	-22.56	-59.1	10.2	66.5
Emerging Markets	22,401	0.4	8.5	0.04	0.06	-0.67	3.84	-16.10	78.6	7.9	41.9
Equity Market Neutral	8,930	3.9	2.4	1.59	2.97	-0.69	4.00	-3.35	81.6	22.4	25.1
Event Driven	11,465	5.0	4.9	1.01	1.78	-0.70	3.04	-7.66	77.1	20.1	20.2
Fixed Income Arbitrage	7,202	5.0	1.7	2.90	6.29	-0.94	4.23	-1.03	54.1	-10.0	68.3
Global Macro	16,824	3.7	2.5	1.46	3.29	0.12	3.54	-2.03	63.2	9.7	68.7
Long/Short Equity Hedge	66,758	4.7	6.2	0.73	1.27	-0.54	3.42	-10.67	89.0	11.1	64.2
Managed Futures	23,471	2.8	7.5	0.36	0.71	0.11	2.28	-14.48	25.4	-12.4	78.4
Multi-Strategy	57,505	5.2	2.5	2.06	4.06	-0.87	5.52	-3.20	80.9	16.3	23.2
Fund of Funds	139,161	1.7	3.5	0.46	0.78	-0.55	2.73	-7.42	79.3	11.6	59.1
All Single Manager Funds	233,194	4.2	4.2	1.00	1.84	-0.39	3.63	-6.36	85.3	11.7	46.8

Table 14: Summary statistics for the pre- and post-crisis returns of the average hedge fund in each Lipper TASS style category, including number of fund months, annualized mean, annualized volatility, Sharpe ratio, Sortino ratio, skewness, kurtosis, maximum drawdown, correlation coefficient with the S&P 500, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags. The pre-crisis period is from January 1996 through December 2006 and the post-crisis period is from January 2010 through December 2014. Sharpe and Sortino ratios are adjusted for the three-month U.S. Treasury Bill rate. The "All Single Manager Funds" category includes the funds in all 10 main Lipper TASS categories and any other single-manager funds present in the database (relatively few) while excluding funds of funds.

market opportunities due to central banking interventions that have changed traditional risk/reward relations among assets.

This potential decrease in leverage is related to the second possible source of apparent underperformance of post-crisis hedge funds: a lower risk-free rate. We estimate that the average risk-free rate declined from 3.80% in the pre-crisis period to 0.07% in the post-crisis period. If hedge funds earn a portion of their return from cash holdings, e.g., as collateral in margin accounts, their post-crisis returns will definitely be affected by the low-interest-rate policies of the world's major central banks, irrespective of manager skill.

Third, hedge-fund database biases are much stronger for older data (see Section 3.2). A researcher who naïvely averaged pre-crisis returns in the Lipper TASS database might introduce an upward bias of 8.6%, whereas post-crisis average returns may only be subject to a 1.9% bias. Unless these biases are corrected before averaging (as we do in this review article), they will tend to exaggerate the difference between pre- and post-crisis hedge-fund returns.

These three factors are sufficient to explain the entirety of the post-crisis underperformance of hedge funds. However, it is still too early to judge whether any or all of these explanations are, in fact, correct. More data must be accumulated before we can come to a definitive conclusion, and these hypotheses provide specific guidelines for the kinds of data that need to be collected.

7.4 Hedge Funds and Systemic Risk

In the aftermath of the Financial Crisis of 2007–2009, the concept of "systemic risk" has emerged as an important phenomenon that goes far beyond its original domain of macroeconomics and central banking policy. Although a review of the systemic risk literature is beyond the scope of this article, the extent to which the hedge-fund industry can offer insights into systemic risk is clearly within our purview.

A natural starting point for developing such insights is to first define and then measure systemic risk—the adage that "one cannot manage what one does not measure" is particularly relevant in this context. Remarkably, five years after one of the worst financial crises since the Great Depression of 1929, we still do not have a consensus on the definition of systemic risk, much less a standardized measure for it. In fact, the review article on systemic risk measures published in this journal by Bisias, Flood, Lo, and Valavanis (2012) lists 31 distinct measures, not one of which is universally endorsed as the canonical measure of systemic risk that should be regularly computed and released by the government. And even after reviewing eight centuries of financial crises, Reinhart and Rogoff's (2009) definitive treatise offers no single barometer with which financial stability can be reliably gauged.

Billio, Getmansky, Lo, and Pelizzon (2012) define systemic risk as the risk of a "systemic event", which is any set of circumstances that threatens the stability of or public confidence in the financial system. This is consistent with the "four L's" of financial crisis—liquidity, leverage, linkages, and losses—that appear repeatedly in various narratives of 2007–2009, and all of these L's touch the hedge-fund industry to some extent. Under this definition, there is little doubt that LTCM's decline in August and September of 1998 was a systemic event, and that the private-sector bailout facilitated by the New York Fed was a reasonable, if somewhat hastily arranged, response. However, in September 2006 when the much larger ($9 billion vs. $4.7 billion) hedge fund Amaranth Advisors shut down because of extreme trading losses, there was no Fed-facilitated bail out and financial markets hardly noticed. Clearly this event was not systemic, and the comparison with LTCM underscores the heterogeneity and complexity of the hedge-fund industry, and the need for more refined analytics to determine how hedge funds may or may not affect systemic risk.

In a series of papers, Chan, Getmansky, Haas, and Lo (2004, 2006, 2007) propose using the hedge-fund industry like a geiger counter to construct measures of systemic risk. Employing aggregate measures of volatility, illiquidity, and financial distress for hedge funds based on statistical regime-switching models, autocorrelation, and linear factor exposures, they show that periods of market dislocation can be predicted to some degree by certain trends in the hedge-fund industry such as regime switches to lower-mean/higher-volatility returns, and increases in illiquidity as measured by asset-weighted autocorrelations.[29]

More recently, Billio, Getmansky, Lo, and Pelizzon (2012) have proposed measures of interconnectedness among four types of financial institutions that figured prominently in the recent financial crisis: banks, broker/dealers, insurance companies, and hedge funds. Using monthly returns for the top 25 institutions in each of these four categories, they estimate common factor exposures using PCA, and estimate pairwise connections using Granger-causality tests. The former technique captures concentrated sources of risk and return across the four sectors, and the latter is used to construct Granger-causality networks, directed graphs that capture both the direction and statistical significance of pairwise relations among financial institutions over time. By applying standard measures of connectivity from social network analysis such as the eigenvector centrality parameter, they conclude that the banking and insurance sectors are particularly important sources of interconnectedness and, therefore, key channels through which systemic events are propagated. Hedge funds are also important nodes in this financial web, but they do not play as large a role in transmitting systemic

[29]Regime-switching models are commonly used in the broader financial economics literature, e.g., Bekaert and Harvey (1995), Ang and Bekaert (2002) and Guidolin and Timmermann (2008) among others.

shocks as banks.[30] A distinct literature focusing on the reverse question—how does systemic risk affect hedge funds?—has developed in parallel. Brunnermeier (2009) argues that hedge funds could be affected by financial crises through many mechanisms: direct exposure, funding liquidity, market liquidity, loss and margin spirals, runs on hedge funds, and aversion to Knightian uncertainty. Some of these mechanisms, like direct exposure and market liquidity, can be captured by hedge fund exposures to market risk factors.

Billio, Getmansky, and Pelizzon (2013) find that liquidity, credit, equities, and equity-market volatility are common risk factors during crises for various hedge-fund strategies.They apply a novel methodology to identify the presence of a common latent risk-factor exposure across all hedge-fund strategies, and find that this latent factor is related to asset and funding liquidity. If the latent risk factor is omitted in risk modeling, the resulting effect of financial crises on hedge fund risk is greatly underestimated. These results support the conclusions of Boyson, Stahel, and Stulz (2010), who document significant contagion from lagged bank- and broker-returns to hedge-fund returns.

Other factors such as funding liquidity, margin spirals, runs on hedge funds, and aversion to Knightian uncertainty are hedge-fund-specific and affect the residual volatility of hedge fund returns (Krishnamurthy (2010)). For example, Khandani and Lo (2007, 2011a) argue that a forced liquidation of a given strategy should increase the strategy volatility through the increase in the residual volatility of hedge fund returns. Billio, Getmansky, and Pelizzon (2013) investigate residual volatility of hedge-fund strategies and show that the increase in this volatility is common among all hedge-fund strategies they consider during the LTCM crisis of 1998 and the Financial Crisis of 2007–2009.

Chan, Getmansky, Haas, and Lo (2004, 2006, 2007), Adrian (2007), and Khandani and Lo (2007, 2011a) show that hedge funds' risk profile during the LTCM crisis was drastically different from other financial crises. Khandani and Lo (2007, 2011a) find an increased correlation among hedge-fund styles in this period and conjecture that this can be due to the increase in systematic linkages with market factors, liquidity, and credit proxies, e.g., the Quant Meltdown of August 2007 (see Section 7.1). Boyson, Stahel, and Stulz (2010) study potential explanations for the clustering of hedge funds' worst returns and find that adverse shocks to asset and funding liquidity as well as contagion may potentially explain this tail risk.

Despite the fact that dislocation in the hedge-fund industry often presages broader fi-

[30]The role of hedge funds in financial crises has been documented in several studies, including Eichengreen, Mathieson, Chadha, Jansen, Kodres, and Sharma (1998), Brown, Goetzmann, and Park (2000), Fung, Hsieh, and Tsatsoronis (2000), Brunnermeier and Nagel (2004), and Chen and Liang (2007). Hedge fund failures and liquidations, and their underlying causes, have also been studied, e.g., Getmansky, Lo, and Mei (2004) and Liang and Park (2010).

nancial crises, it is easy to miss or ignore these early warning signs. Although academic studies raised the possibility of crisis as early as 2004 and 2005 (see Chan, Getmansky, Haas, and Lo (2004), Rajan (2005), Shiller (2005), and Section 7.1), these were outliers with respect to the financial industry's perspective at the time. A sense for the magnitude of the gulf between academia and industry can be obtained from the views of the Counterparty Risk Management Policy Group II (CRMPG-II) (2005), a non-profit industry consortium with the following mandate: "The primary purpose of CRMPG-II—building on the 1999 report of CRMPG-I—is to examine what additional steps should be taken by the private sector to promote the efficiency, effectiveness and stability of the global financial system". The CRMPG-II was chaired by Gerald Corrigan, then a managing director at Goldman Sachs, and the two vice chairs were Don Wilson, then Chief Risk Officer of JP Morgan, and David Bushnell, then senior risk officer of Citigroup. The other members of the policy group included senior representatives from top financial institutions and their law firms: Bear Stearns, Cleary Gottlieb Steen & Hamilton, Deutsche Bank, General Motors Asset Management, HSBC, Lehman Brothers, Merrill Lynch, Morgan Stanley, TIAA-CREF, and Tudor Investment Corporation. On July 25, 2005, this body of industry experts published their report which began with the following summary assessment (CRMPG-II (2005, p. 1)):

> In approaching its task, the Policy Group shared a broad consensus that the already low statistical probabilities of the occurrence of truly systemic financial shocks had further declined over time.

While this statement may seem naïve with the benefit of hindsight, it must be emphasized that business was booming during this period, with many of the firms represented in the CRMPG-II earning record profits that year and the year after. However, even in this context, the CRMPG-II report contains some prescient warnings that the members both documented and then dismissed with their blanket assessment. Recommendations 12, 21, and 22 of the report called for industry-wide efforts to: (1) cope with serious "back-office" and potential settlement problems in the CDS market; and (2) stop the practice whereby some market participants "assign" their side of a trade to another institution without the consent of the original counterparty to the trade.[31] The first recommendation was for the largest institutions to catch up on the one-year backlog in simply entering into their record-keeping and, presumably, their risk-management systems, the terms of CDS contracts they had executed. The second recommendation was to address the fact that a number of CDS contracts could legally be reassigned to other counterparties without prior approval or notification, making

[31] See CRMPG-II (2005, p. iv).

it virtually impossible to determine the counterparty credit risk of such contracts.[32] These recommendations seem grossly inconsistent with the CRMPG-II's conclusion that the risk of a systemic shock had declined.

This example highlights the challenges that the financial industry faces in identifying threats to financial stability; such threats are often forged in the crucible of highly profitable, rapidly growing business lines. Unless corporate executives have perfect timing, it is unrealistic to expect them to reduce risk as their businesses are expanding, nor will shareholders support such behavior. While the concept of countercyclical capital buffers seems sensible, it is virtually impossible for them to be self-imposed by the industry. Therefore, macroprudential regulation can play a positive role in creating a more stable and robust financial system.

8 Implementation Issues for Hedge Fund Investing

Having reviewed much of the academic hedge-fund literature in Sections 2–7, we now turn to four implementation issues facing hedge-fund investors. In Section 8.1, we consider the potential dangers of mindlessly applying traditional mean-variance portfolio analysis to hedge fund returns. The multi-faceted nature of hedge-fund risk exposures, the smoothness of certain hedge-fund returns due to illiquidity, and the nonstationarity of their return distributions imply that standard mean-variance analysis can yield highly misleading portfolio allocations, especially at the asset-class level.

A related problem is discussed in Section 8.2 involving the potential over-diversification of hedge-fund portfolios, which can lead to lower expected returns and, surprisingly, greater risks. The investment implications of adding hedge funds to a portfolio of traditional assets are discussed in Section 8.3. Given the potential pitfalls in hedge-fund investing, the need for a more systematic framework for making alternative investment decisions is clear and in Section 8.4 we present such a framework.

From a broader perspective, investing in hedge funds seems at odds with much of the academic investments literature which emphasizes passive risk premia and dismisses the possibility of consistent sources of alpha. However, the popularity of hedge funds among large institutional investors who also invest passively suggests a troubling contradiction between theory and practice. In Section 8.5, we provide a review of the Adaptive Markets Hypothesis, an alternative to the Efficient Markets Hypothesis that reconciles this contradiction in an

[32]Both of these problems were not isolated issues, but were so widespread that eventually Timothy Geithner, then president of the New York Fed, was motivated to intervene through moral suasion to get the financial industry to address these concerns.

intellectually satisfying manner.

8.1 The Limits of Mean-Variance Optimization

A common question facing investors, advisers, and institutional money managers is how much should they allocate to hedge funds? Many turn to mathematical optimization tools only to discover that their optimizer recommends a 200% allocation to hedge funds and −100% allocation to other assets. Such results are usually disregarded, and rightly so. While hedge funds may be desirable investments for some investors, biases in hedge fund reporting artificially boost historical estimates of expected returns while autocorrelation due to illiquid portfolios artificially dampens estimated variances and covariances. Furthermore, optimizers may produce recommendations that are fine-tuned for a previous period but poorly suited for the future, and the resulting portfolios may have unsuitable risk characteristics.

In Table 15 we show that a (nearly) unconstrained optimizer can produce a portfolio that would have earned an amazing 40.4% per year between 1996 and 2014. However, the investments required for such a portfolio are not even feasible: the optimizer calls for short exposure to certain hedge fund categories. Nevertheless, mathematical optimizers can be a useful guide for investors, calling attention to assets that have historically had desirable average returns, low correlation, or other characteristics. It is usually helpful to constrain the set of solutions from which the optimizer may choose, preemptively eliminating solutions that are too risky, too illiquid, involve too much leverage, or are outside the feasible investment universe. In Table 15 we show a number of mean-variance-optimized portfolio weights subject to such constraints. Results toward the top of the table are generally more constrained and are probably a better guide to the sorts of choices a prudent investor might have made during the previous 19 years.

In addition to the traditional constraint on the portfolio's standard deviation, we employ a more novel constraint on portfolio autocorrelation in an effort to avoid portfolios that are likely to be too illiquid. While some endowments may be able to tolerate an illiquid portfolio because their investment horizon is presumably unbounded, individual investors often need to access their assets sooner and may choose to be more cautious about illiquidity. See Section 5.4 for further discussion about mean-variance-illiquidity optimization.

8.2 Over-Diversification

The proliferation of multi-strategy funds and funds of funds over the past two decades has given investors an unprecedented amount of diversification within the hedge-fund industry

Optimization Parameters			Characteristics of Optimal Portfolio			Optimal Portfolio Weights													
Maximum Volatility	Maximum Auto-correlation	Shorting Constraints	Optimized Annualized Return	Optimized Annualized Volatility	Optimized Auto-correlation	3 Month Treasury Bills	S&P 500 Total Return Index	Barclay U.S. Aggregate Bond Index	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity Hedge	Managed Futures	Multi-Strategy	Fund of Funds
0.05	0.1	Long Only	6.8%	5.0%	0.10	0.00	0.15	0.54	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.30	0.00	0.00	0.00
0.05	0.25	Long Only	6.8%	5.0%	0.17	0.00	0.12	0.43	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.27	0.00	0.00	0.00
0.05	0.4	Long Only	6.8%	5.0%	0.17	0.00	0.12	0.43	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.27	0.00	0.00	0.00
0.1	0.1	Long Only	8.2%	10.0%	0.10	0.00	0.54	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00
0.1	0.25	Long Only	8.3%	10.0%	0.16	0.00	0.34	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.00
0.1	0.4	Long Only	8.3%	10.0%	0.16	0.00	0.34	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.00
0.15	0.1	Long Only	9.4%	15.0%	0.09	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00
0.15	0.25	Long Only	9.4%	15.0%	0.09	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00
0.15	0.4	Long Only	9.4%	15.0%	0.09	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00
0.2	0.1	Long Only	9.4%	15.4%	0.08	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.2	0.25	Long Only	9.4%	15.4%	0.08	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.2	0.4	Long Only	9.4%	15.4%	0.08	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.05	0.1	Can Short T-bills	8.6%	5.0%	0.10	-1.06	0.03	1.12	0.00	0.13	0.00	0.27	0.24	0.00	0.01	0.22	0.04	0.00	0.00
0.05	0.25	Can Short T-bills	8.8%	5.0%	0.17	-1.11	0.02	1.03	0.00	0.12	0.00	0.37	0.42	0.00	0.00	0.14	0.02	0.00	0.00
0.05	0.4	Can Short T-bills	8.8%	5.0%	0.16	-1.12	0.02	1.03	0.00	0.12	0.00	0.39	0.40	0.00	0.00	0.14	0.02	0.00	0.00
0.1	0.1	Can Short T-bills	14.8%	10.0%	0.10	-3.09	0.06	2.22	0.00	0.26	0.00	0.49	0.50	0.00	0.00	0.47	0.09	0.00	0.00
0.1	0.25	Can Short T-bills	15.0%	10.0%	0.16	-3.25	0.04	2.05	0.00	0.25	0.00	0.78	0.79	0.00	0.00	0.30	0.03	0.00	0.00
0.1	0.4	Can Short T-bills	15.0%	10.0%	0.17	-3.23	0.04	2.05	0.00	0.25	0.00	0.74	0.83	0.00	0.00	0.29	0.03	0.00	0.00
0.15	0.1	Can Short T-bills	20.8%	15.0%	0.10	-5.16	0.08	3.33	0.00	0.39	0.00	0.81	0.67	0.00	0.00	0.74	0.13	0.00	0.00
0.15	0.25	Can Short T-bills	21.2%	15.0%	0.17	-5.36	0.06	3.08	0.00	0.37	0.00	1.16	1.21	0.00	0.00	0.43	0.05	0.00	0.00
0.15	0.4	Can Short T-bills	21.2%	15.0%	0.17	-5.36	0.06	3.07	0.00	0.37	0.00	1.16	1.19	0.00	0.00	0.45	0.05	0.00	0.00
0.2	0.1	Can Short T-bills	26.9%	20.0%	0.10	-7.20	0.11	4.43	0.00	0.53	0.00	1.06	0.88	0.00	0.00	1.01	0.17	0.00	0.00
0.2	0.25	Can Short T-bills	27.4%	20.0%	0.17	-7.51	0.08	4.10	0.00	0.48	0.00	1.56	1.55	0.00	0.00	0.55	0.06	0.14	0.00
0.2	0.4	Can Short T-bills	27.4%	20.0%	0.17	-7.49	0.08	4.09	0.00	0.50	0.00	1.57	1.57	0.00	0.00	0.61	0.06	0.00	0.00
0.05	0.1	Can Short Anything	12.0%	5.0%	0.10	-0.60	-0.06	0.75	-0.46	0.16	0.11	0.03	0.86	0.25	0.21	0.72	0.09	0.76	-1.82
0.05	0.25	Can Short Anything	12.1%	5.0%	0.14	-0.55	-0.06	0.76	-0.40	0.15	0.12	0.01	0.92	0.19	0.20	0.69	0.10	0.74	-1.88
0.05	0.4	Can Short Anything	12.1%	5.0%	0.14	-0.54	-0.06	0.76	-0.40	0.15	0.12	0.01	0.92	0.20	0.21	0.69	0.10	0.73	-1.89
0.1	0.1	Can Short Anything	21.4%	10.0%	0.10	-2.27	-0.12	1.50	-0.96	0.33	0.20	0.09	1.77	0.49	0.38	1.42	0.19	1.48	-3.50
0.1	0.25	Can Short Anything	21.5%	10.0%	0.14	-2.15	-0.11	1.51	-0.80	0.32	0.20	0.07	1.88	0.35	0.37	1.37	0.21	1.46	-3.66
0.1	0.4	Can Short Anything	21.5%	10.0%	0.14	-2.14	-0.11	1.51	-0.80	0.31	0.21	0.06	1.87	0.36	0.37	1.36	0.21	1.46	-3.68
0.15	0.1	Can Short Anything	30.8%	15.0%	0.10	-3.91	-0.18	2.23	-1.43	0.50	0.29	0.15	2.61	0.71	0.56	2.17	0.28	2.25	-5.23
0.15	0.25	Can Short Anything	31.0%	15.0%	0.14	-3.71	-0.16	2.25	-1.21	0.48	0.31	0.11	2.79	0.50	0.53	2.07	0.31	2.22	-5.49
0.15	0.4	Can Short Anything	31.0%	15.0%	0.15	-3.71	-0.17	2.26	-1.20	0.47	0.31	0.09	2.80	0.54	0.55	2.05	0.31	2.19	-5.50
0.2	0.1	Can Short Anything	40.2%	20.0%	0.10	-5.54	-0.24	2.98	-1.92	0.66	0.38	0.21	3.45	0.94	0.74	2.90	0.36	3.02	-6.95
0.2	0.25	Can Short Anything	40.4%	20.0%	0.14	-5.26	-0.22	3.03	-1.64	0.64	0.42	0.14	3.70	0.65	0.69	2.79	0.40	2.94	-7.30
0.2	0.4	Can Short Anything	40.4%	20.0%	0.14	-5.27	-0.22	3.01	-1.62	0.64	0.41	0.15	3.71	0.66	0.70	2.77	0.41	2.95	-7.30

Table 15: Results of Markowitz mean-variance optimization over the period January 1996 through December 2014. The variably-colored columns show the optimal portfolio weights and the adjacent blue columns show the optimized portfolios expected arithmetic rate of return, volatility, and autocorrelation. Large long positions are colored green while large short positions are colored red; intermediate positions are colored yellow. Each row corresponds to a different set of constraints on volatility, liquidity (using autocorrelation as an indicator), and shorting.

(Learned and Lhabitant (2003) and Amo, Harasty, and Hillion (2007)). However, the Financial Crisis of 2007–2009 has called into question the view that hedge funds are really "hedged", and that diversification across hedge-fund styles is beneficial. Billio, Getmansky, and Pelizzon (2013) find that the average correlation among hedge-fund strategies jumped from 0.32 in August 2008 to 0.52 in September 2008, a 64% increase. At the same time, the average returns of most hedge funds have declined significantly (see Section 7.3), leaving investors wondering whether hedge-fund investing is still worthwhile.

Cumming, Dai, and Shawky (2012) show that on a risk-adjusted basis, hedge funds that diversify across sectors and asset classes outperform other funds by an average of 1.6% per year. However, diversification across styles is found to exhibit a significant negative association with hedge fund returns. Nevertheless, for funds of funds, the authors find a significant positive relation between performance and diversification across sectors, styles, and geographies.

In documenting the performance of the hedge-fund industry from 1995 to 2004, Fung, Hsieh, Naik, and Ramadorai (2008) find that, on average, funds of funds deliver alpha only in the period between October 1998 and March 2000, although a subset of funds of funds do seem to have consistent alpha.

Furthermore, Brown, Gregoriou, and Pascalau (2011) find that the variance-reducing effects of diversification become insignificant once a fund of funds holds more than 20 underlying hedge funds. Yet the majority of funds of funds are more diversified than this. They find that over-diversification by funds of funds can increase left-tail risk exposure and lower expected returns, especially when hedge fund returns are smoothed. This increase in tail risk is accompanied by lower returns, which they attribute to the cost of necessary due diligence, a drag on performance that increases with the number of underlying hedge funds in portfolio.

8.3 Investment Implications

Reviewing the performance characteristics of hedge funds has provided ample evidence to support the view that investors selecting their strategic asset allocations should not consider hedge funds to be a monolithic category. The decision to allocate assets to a hedge fund strategy should involve the consideration of a number of factors. First, of course, is a strategy's potential for contributing positive returns—determining this factor we leave solely to the investor. But just as important is the investor's consideration as to which hedge fund risks she can best afford to add to her portfolio. Are occasional large losses acceptable? Is an investment uncorrelated with equities preferable? What volatility is acceptable? Are correlated strategies already in her portfolio? Our results suggest that while many hedge fund categories have similar characteristics, they are different enough that an investor in alternatives should pause and determine which investment styles are most consistent with her risk preferences.

If an investor sought to simply maximize expected returns without regard for risk, her investment procedure would be simple: forecast the returns of each candidate investment and allocate 100% of her assets to the investment associated with the highest expected return. However, most investors are concerned about the risk of large losses. To limit the potential for large losses, investors tend to exploit at least one of two strategies: first, they generally spread their capital across a number of investments that they expect to produce good returns in the hope that not all of the investments will simultaneously decline in value (diversification). And second, they may choose to allocate more of their assets to investments that they deem less likely to experience large price decreases. The implementation of these two risk mitigation strategies is often based on forecasts of volatility and correlation. While a good starting place, this approach falls short when one contemplates investments whose distributions are likely to have non-zero higher moments (of particular concern is the combination of positive excess kurtosis and negative skewness, a combination that reflects a history of large sudden losses). Unfortunately, this encompasses nearly all of the investments considered thus far, including, to a degree, stocks and bonds (see Table 16).

From 1996 to 2014	# fund-months	Annualized Mean	Annualized Volatility	Sharpe Ratio	Sortino Ratio	Skewness	Kurtosis	Maximum DD	S&P 500 Correl.	ac(1)	Box-Q(3) p-value
S&P 500 Total Return Index	228	8.6%	15.4%	0.38	0.61	-0.67	4.00	-50.9%	1.00	0.08	0.27
Barclays U.S. Aggregate Index	228	5.6%	3.5%	0.85	1.56	-0.32	4.00	-3.8%	-0.01	0.07	0.02
60/40 Stocks/Bonds	228	7.7%	9.3%	0.54	0.88	-0.67	4.30	-32.5%	0.99	0.06	0.25

Table 16: Summary statistics for the stock, bond, and 60/40 stocks/bonds portfolios from January 1996 through December 2014. The number of months, annualized mean, annualized volatility, Sharpe ratio, Sortino ratio, skewness, kurtosis, maximum drawdown, correlation coefficient with the S&P 500, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags are calculated for the S&P 500 Total Return Index (stock portfolio), Barclays U.S. Aggregate Index (bond portfolio), and 60/40 stocks/bonds portfolio.

Investors' confidence in the traditional 60% stocks, 40% bonds portfolio seems to have declined in recent years. The brutal stock market slumps bookending the recent decade seem to have erased the investing euphoria of the 90s, while a suspicion that interest rates may reverse their decades-long trend and plateau, or even rise, tempers interest in bonds. Thus ever more investors are asking whether they should allocate a portion of their portfolios to "alternatives"—generally defined as anything other than stocks, bonds, and cash. For many investors, especially high-net-worth investors, pension funds, and endowments, investing in alternatives may include an allocation to hedge funds.

Table 16 reports performance statistics for the S&P 500 Total Return Index (stock portfolio), Barclays U.S. Aggregate Index (bond portfolio), and 60/40 stocks/bonds portfolio for the period January 1996 through December 2014. Over the past 19 years both stock and bond asset classes have produced attractive returns, albeit at strikingly different volatilities. Because U.S. interest rates have declined over this period, some argue that the extremely attractive risk-reward ratio of bonds should be viewed with an extra dose of skepticism when making decisions about future asset allocations. Although the returns of stocks and bonds are hardly IID normal, in comparison to the returns of most hedge fund investment styles they look well-behaved, having relatively modest kurtosis, negative skewness, and autocorrelation. Interestingly enough, the average return (and Sharpe ratio) of hedge funds over this period falls between that of stocks and bonds (see Table 6). In Table 16 we also summarize the simulated performance of a prototypical 60% stocks, 40% bonds portfolio (with free monthly rebalancing) based on these two indexes. Note that the resulting two-asset portfolio, while less volatile, is still highly correlated with equities. Geczy (2014) finds similar results—from 1999 through 2013, the correlation of returns between a 60/40 portfolio and a 100% equity portfolio was 0.98. Even if an investor invests 30% in stocks and 70% in bonds, the resulting correlation with a 100% stock portfolio is 0.85. As a result, a long-only stock and bond portfolio is not particularly well diversified.

Table 17 shows that reallocating 5%, 10%, 20%, or 50% from a 60/40 portfolio into the (non-investable) "average" hedge fund would have decreased a traditional portfolio's volatility more than its returns. The combined effect is to increase the risk-adjusted excess return by roughly 13%. Actual investors' experiences, of course, would have varied based on how similar their investment choices were to this average (and monthly-rebalanced) measure of hedge fund returns, fees, and the tracking error associated with their stock and bond investments. It is worth noting that many investors seeking a diverse exposure to hedge funds choose to invest through a fund of funds, which, on average, would have resulted in inferior returns (see Table 18).

Returning briefly to our earlier theme of hedge-fund style heterogeneity, we also simulated

From 1996 to 2014	# fund-months	Annualized Mean	Annualized Volatility	Sharpe Ratio	Sortino Ratio	Skewness	Kurtosis	Maximum DD	S&P 500 Correl.	ac(1)	Box-Q(3) p-value
60% Stocks, 40% Bonds, 0% HF	228	7.7%	9.3%	0.54	0.88	-0.67	4.30	-32.5%	0.99	0.06	0.25
57% Stocks, 38% Bonds, 5% HF	228	7.6%	9.1%	0.54	0.90	-0.70	4.35	-32.0%	0.99	0.07	0.25
54% Stocks, 36% Bonds, 10% HF	228	7.6%	8.9%	0.55	0.91	-0.72	4.40	-31.4%	0.99	0.07	0.25
48% Stocks, 32% Bonds, 20% HF	228	7.5%	8.4%	0.57	0.93	-0.77	4.52	-30.2%	0.99	0.09	0.23
30% Stocks, 20% Bonds, 50% HF	228	7.1%	7.2%	0.61	0.99	-0.86	4.95	-26.6%	0.95	0.14	0.10

Table 17: Summary statistics for the 60%/40%/0%, 57%/38%/5%, 54%/36%/10%, 48%/32%/20%, and 30%/20%/50% stock/bond/hedge fund portfolios from January 1996 through December 2014. The number of months, annualized mean, annualized volatility, Sharpe ratio, Sortino ratio, skewness, kurtosis, maximum drawdown, correlation coefficient with the S&P 500, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags are calculated for each portfolio.

the performance of a 48/32/20 stock/bond/hedge fund portfolio in which 20% of the assets were allocated to one specific hedge-fund style (see Table 18). In some cases this would have resulted in returns similar to those of the 60/40 stocks/bonds portfolio, earned a lower volatility, and had a smaller maximum drawdown (e.g., Event Driven and Long/Short Equity Hedge). In other cases, it would result in a similar level of volatility and returns (Emerging Markets). The impact on the return distributions' kurtosis is particularly varied, as some portfolios have nearly no kurtosis while others have heavy tails.

As before, these simulations are based on the average return of funds within a category and on portfolios rebalanced monthly. Both of these assumptions are likely to make the simulated results look more attractive. It is interesting that, even with this advantage, adding a 20% average hedge-fund allocation to a 60/40 portfolio would not have increased the portfolio's average (non-risk-adjusted) rate of return, despite the popular conception that hedge funds regularly earn outsized returns. We note that many hedge-fund index calculators, following a different methodology than our bias adjustments (see Section 3.2), report more attractive returns for the industry. For example, Geczy (2014) shows that adding a 15% allocation to alternatives and 5% each to alternative equity and alternative fixed-income investments decreases total portfolio risk and increases expected returns.

In summary, the historical data show that hedge funds have not, on average, meaningfully

From 1996 to 2014	# fund-months	Annualized Mean	Annualized Volatility	Sharpe Ratio	Sortino Ratio	Skewness	Kurtosis	Maximum DD	S&P 500 Correl.	ac(1)	Box-Q(3) p-value
60% Stocks, 40% Bonds, 0% HF	228	7.7%	9.3%	0.54	0.88	-0.67	4.30	-32.5%	0.99	0.06	0.25
48% Stocks, 32% Bonds, 20% Convertible Arbitrage	228	7.3%	8.3%	0.55	0.89	-1.00	6.51	-32.0%	0.98	0.14	0.06
48% Stocks, 32% Bonds, 20% Dedicated Short Bias	228	6.3%	5.8%	0.64	1.09	-0.67	5.18	-20.5%	0.89	0.02	0.34
48% Stocks, 32% Bonds, 20% Emerging Markets	228	7.6%	9.5%	0.52	0.82	-0.96	5.49	-34.1%	0.97	0.10	0.22
48% Stocks, 32% Bonds, 20% Equity Market Neutral	228	7.1%	7.7%	0.58	0.95	-0.80	4.80	-28.8%	0.99	0.10	0.13
48% Stocks, 32% Bonds, 20% Event Driven	228	7.6%	8.3%	0.59	0.96	-0.86	4.95	-31.0%	0.99	0.11	0.14
48% Stocks, 32% Bonds, 20% Fixed Income Arbitrage	228	7.2%	7.8%	0.58	0.95	-0.92	5.70	-29.8%	0.98	0.09	0.15
48% Stocks, 32% Bonds, 20% Global Macro	228	7.2%	7.9%	0.58	0.97	-0.59	3.90	-26.7%	0.98	0.06	0.35
48% Stocks, 32% Bonds, 20% Long/Short Equity Hedge	228	7.7%	8.9%	0.57	0.94	-0.73	4.26	-31.0%	0.98	0.09	0.23
48% Stocks, 32% Bonds, 20% Managed Futures	228	7.3%	7.7%	0.60	1.05	-0.44	3.24	-23.9%	0.95	0.02	0.57
48% Stocks, 32% Bonds, 20% Multi-Strategy	228	7.4%	8.1%	0.58	0.95	-0.80	4.71	-30.4%	0.98	0.08	0.24
48% Stocks, 32% Bonds, 20% Fund of Funds	228	6.9%	8.2%	0.52	0.84	-0.80	4.63	-30.4%	0.98	0.08	0.26
48% Stocks, 32% Bonds, 20% All Single Manager Funds	228	7.5%	8.4%	0.57	0.93	-0.77	4.52	-30.2%	0.99	0.09	0.23

Table 18: Summary statistics for the 60%/40%/0% and 48%/32%/20% stock/bond/hedge fund portfolios from January 1996 through December 2014. The number of months, annualized mean, annualized volatility, Sharpe ratio, Sortino ratio, skewness, kurtosis, maximum drawdown, correlation coefficient with the S&P 500, first-order autocorrelation, and p-value of the Ljung-Box Q-statistic with three lags are calculated for each portfolio. The 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database are considered in the hedge-fund allocation.

outperformed traditional portfolios of stocks and bonds after fees. On average, once returns have been adjusted for various sampling biases (see Section 3.2), hedge funds do not routinely generate double-digit returns. However, the ride for hedge-fund investors has generally been smoother: as a group, hedge funds have exhibited lower volatility than traditional stock/bond portfolios. In addition, there are a number of styles of hedge fund investing. While many are correlated and have much in common, on the whole they are a heterogeneous lot: some are as dissimilar as stocks and bonds. This is consistent with Brown and Goetzmann (2003) who find that hedge funds are a reasonably heterogeneous group and present distinct styles. Based on historical data, some styles of hedge fund investing result in higher volatility, and some lower; some are correlated with equities, and some not; and some have a high propensity to occasionally experience large losses, while others experience this to a lesser extent. Liang (2004) studies asset allocation among hedge funds, funds of funds, and CTAs. He shows that CTAs are a natural hedge for equity investments especially during market declines; CTAs have relatively low correlations with hedge funds and funds of funds, and they have very different characteristics from most hedge funds (see also Kaminski (2011)). We propose a more systematic approach to alternative investing in the next section.

8.4 An Integrated Hedge-Fund Investment Process

Investing in hedge funds has changed considerably over the last two decades as the population of investors has grown beyond family offices, foundations, endowments, and high net worth investors to include more traditional institutional investors such as pension funds, sovereign wealth funds, and investment consultants. This shift in the investor base has brought new tools, policies, and procedures to the hedge-fund industry because today's institutional investors require an unprecedented degree of transparency, accountability, and repeatability, i.e., they require an *investment process*, not just the ability to select a portfolio of hedge funds. Although in the past many institutional investors relied primarily on the qualitative judgments that funds of funds managers offer, institutional investors today often prefer a more systematic approach to making manager-selection decisions, as well as broader asset-allocation decisions among various hedge-fund style categories.

Several systematic approaches have been proposed, largely led by practitioners from the hedge-fund and funds of funds industry, and these approaches fall loosely into two groups: top-down and bottom-up investment processes.

Goldman, Sachs & Co. and Financial Risk Management Ltd. (1999) develop a top-down absolute-return framework emphasizing diversification across as well as within hedge-fund strategies, with the primary constraint being the investor's ability to monitor multiple managers. Bein and Wander (2002) propose a top-down risk allocation framework that allows investors to explicitly integrate active management decisions and hedge-fund risks into a traditional overall asset allocation process. Chung, Rosenberg, and Tomeo (2004) provide another top-down hedge-fund asset allocation process by dividing hedge-fund strategies into two classes: convergent strategies that benefit from small temporary mispricings, which are short volatility, and divergent strategies that exploit larger and longer-horizon market inefficiencies, which are long volatility. Given that divergent strategies tend to be profitable during periods of heightened volatility and economic uncertainty, the authors argue that allocating assets to both types of strategies can improve expected returns and reduce risk.

Several studies propose a bottom-up approach to constructing hedge-fund portfolios. Zask (2000) describes a method for hedge-fund valuation based on management fees, performance fees, and discounted cash flows analysis. Stemme and Slattery (2002) outline the practical considerations involved in selecting individual hedge funds, hiring a consultant, or investing in a fund of funds, including costs, control, track record, and capacity issues. And Clark and Winkelmann (2004) develop a framework where all hedge funds are analyzed based on how much of the projected performance is due to market movements, due to manager skill, and whether an investor is confident in the manager's (or strategy's) ability to continue to deliver performance.

A hybrid approach proposed by Lo (2008) combines qualitative judgment with quantitative methods, a particularly important feature for investing in complex, multi-faceted, and highly heterogeneous assets such as hedge funds. This combination is achieved through a two-stage investment process in which a top-down asset allocation decision to broad hedge-fund categories is coupled with bottom-up manager-selection decisions within each category. Although a two-stage investment process is generally sub-optimal relative to a single-stage optimization, the complexities and qualitative aspects of hedge-fund investing make a two-stage approach more robust and easier to implement. This investment process is based on a set of six basic design principles:

- The target expected return for each strategy should be commensurate with the risks of that strategy—higher-risk strategies should have higher target expected returns.
- The uses of funds should determine the target expected return, not the sources of capital.
- In evaluating the risk/reward ratio for each strategy, return autocorrelation and illiquidity exposure should be taken into account explicitly. In particular, the Sharpe ratios of strategies with large positively serially correlated returns should be deflated (see Lo

(2001), Getmansky, Lo, and Makarov (2004), and Section 5 for details).

- Qualitative judgments about managers, strategies, and market conditions are valuable inputs into the capital allocation process that no quantitative models can replace, but those judgments should be integrated in a systematic and consistent fashion with quantitative methods.

- Risk and performance attribution should be performed on a regular basis for and by each manager, as well as for the entire portfolio.

- Risk limits and related guidelines for each manager should be consistent across time and across managers, and should be communicated clearly to all managers on a regular basis.

These design principles, coupled with insights from traditional portfolio management theory and practice, imply a portfolio optimization component in which required or "target" expected returns and variances are determined in advance by investor mandates and market conditions, covariances are estimated via econometric methods and modified by qualitative judgment, and then asset-class allocations are determined by minimizing variance subject to an expected-return constraint. Within each asset class, manager-specific allocations are determined by incorporating qualitative information into the investment process through a scoring process. The seven components of this quantitative/qualitative investment process, which we shall refer to as QQIP for convenience, are depicted in Figures 7 and 8 and given by:

(i) Define asset classes by strategy.
(ii) Set target portfolio expected return, μ_o, and desired volatility, σ_o.
(iii) Set target expected returns and risks for asset classes.
(iv) Determine correlations via econometric analysis.
(v) Compute minimum-variance asset-class allocations subject to μ_o constraint.
(vi) Allocate capital to managers within each asset class.
(vii) Monitor performance and risk budgets, and re-optimize as needed.

Although Lo (2008) provides detailed discussions for each of these steps, he emphasizes that this framework is meant to serve only as a starting point for designing a suitable alternative investment process. Because of the heterogeneity of the hedge-fund industry and the variability of investment objectives and constraints among investors, there is no single investment process that fits all investors.

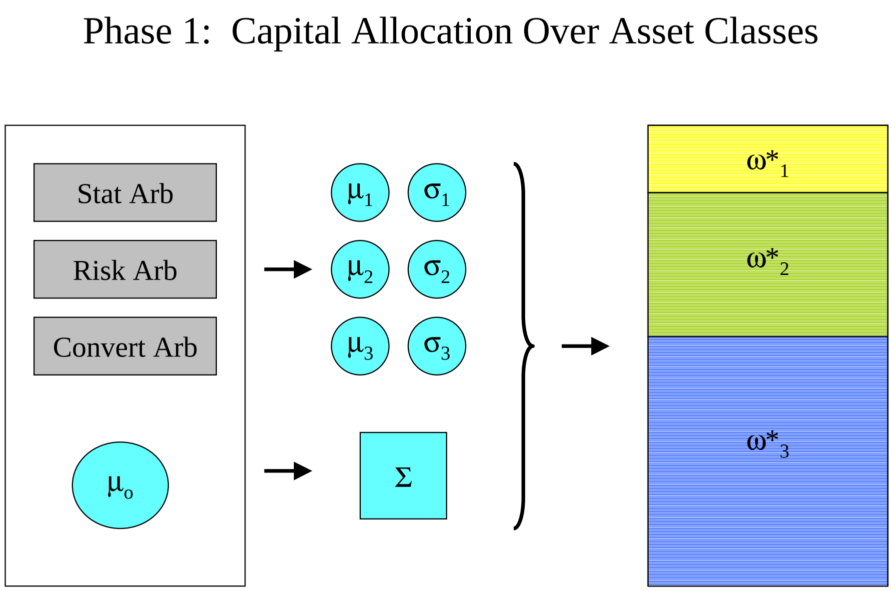


Figure 7: First stage of a quantitative/qualitative capital allocation algorithm for alternative investments, in which asset classes are defined and optimal asset-class weights are determined as a function of target expected returns and risk levels, and an estimated covariance matrix.

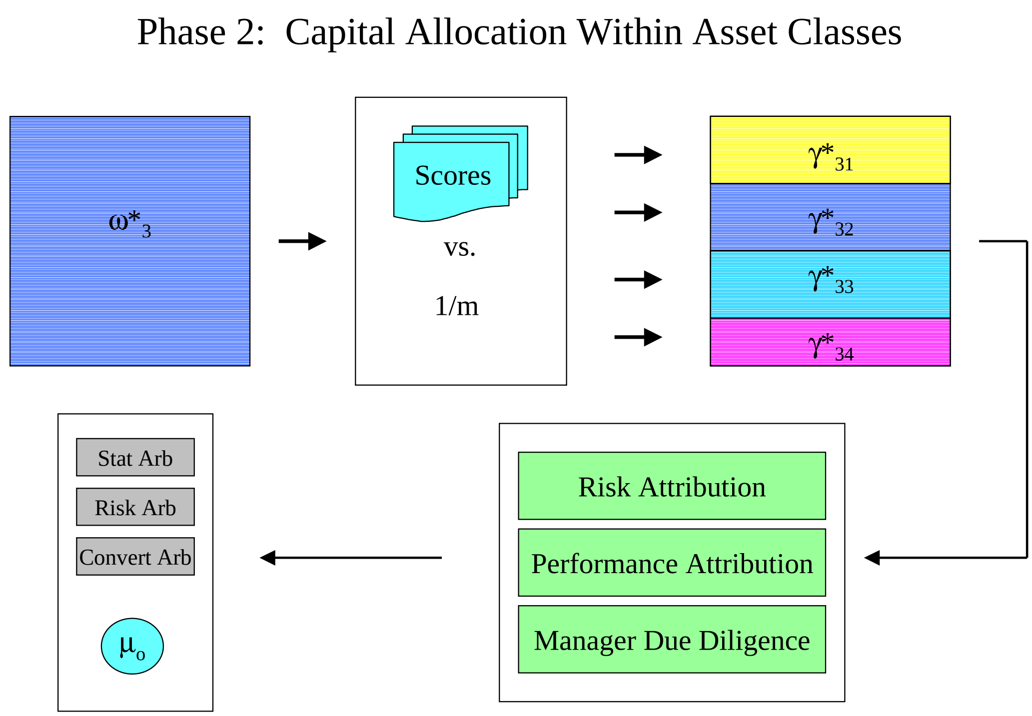


Figure 8: Second stage of a quantitative/qualitative capital allocation algorithm for alternative investments, in which capital is allocated to managers within an asset class according to a scoring procedure that incorporates qualitative as well as quantitative information.

The first step in QQIP is to define the universe of all hedge funds into a smaller set of categories where managers in each category pursue relatively homogeneous styles of investing. An example of such categories is the Lipper TASS classification used throughout this survey and described in the Appendix, but finer stratifications may be appropriate, depending on the investment objectives of the investor and the size of the assets to be deployed.

The second step is to set a target expected return, desired level of risk, and acceptable loss limits or maximum drawdown for the entire portfolio. While these parameters are, by nature, rather ambiguous quantities when discussed among investment committee members and investment officers, such discussions are invaluable in setting realistic expectations for what a portfolio of hedge funds can offer.

Once these high-level parameters (or ranges of parameters) have been specified, the third step is to do the same for the categories specified in the first step. This requires more specialized knowledge of both the historical performance of individual categories of hedge funds and how the categories are currently positioned. One way to develop target expected returns and volatilities for hedge fund categories is to estimate linear factor models for category indexes (see Section 6), and then to develop target expected returns and volatilities for the factors. In many cases, it is easier to develop prospective intuition for the likely behavior of factors such as liquidity, credit, the business cycle, and exchange ratios than for hedge-fund category index returns.

Given the target expected returns and volatilities of the hedge-fund categories in the investment universe, the next step in QQIP is to estimate the correlation matrix among the index returns of the hedge-fund categories. This may seem straightforward from a statistical perspective—use the standard estimator with historical data or a linear factor model estimator that requires fewer estimated parameters (see Section 6.2). However, the fact that correlations can change in response to market conditions makes this step more challenging, requiring qualitative input to adjust the correlations to reflect current market conditions that might not yet be reflected in historical time series estimators.[33] In such cases, qualitative adjustments to the correlation matrix of category-index returns may be necessary, but it must be kept in mind that arbitrary changes to entries in a correlation matrix could violate the positive semidefiniteness of the matrix. If such violations are ignored, the outcome of a portfolio optimization using such a matrix could yield nonsensical results such as negative variances. To avoid these pathologies, it is possible to compute the positive semidefinite correlation matrix that is "closest" to the qualitatively adjusted correlation

[33]For example, during periods of macroeconomic stress, U.S. equities become more highly correlated with foreign currency movements, hence correlations between long/short equity managers and foreign currency traders may be higher than historical estimates would imply if economic conditions deteriorate.

matrix using methods developed by Higham (2002) and Qi and Sun (2006).

Once the target expected returns, volatilities, and correlations among the hedge-fund categories have been determined, the next step in QQIP is to construct an optimal portfolio. There are several methods for doing so—see, for example, Brennan, Lo, and Nguyen (2015)—but a natural starting point is to find the asset allocation over hedge-fund categories that minimizes the portfolio variance subject to the target portfolio expected return constraint specified in step 1. For most fund-of-fund and multi-manager applications, it is also necessary to impose non-negativity constraints on the portfolio weights since it is typically impossible to establish a "short" position in a manager. However, as long as the target expected returns are realistic and the covariance matrix is well-behaved, (19) should yield non-negative portfolio weights.[34]

$$\underset{\boldsymbol{\omega}}{\text{Min}}\ \tfrac{1}{2}\,\boldsymbol{\omega}'\boldsymbol{\Sigma}\boldsymbol{\omega} \ \ \text{subject to} \ \ \boldsymbol{\omega}'\boldsymbol{\mu} \geq \mu_o \ \ \text{and} \ \ \boldsymbol{\omega}'\boldsymbol{\iota} = 1 \ . \tag{18}$$

The solution to (18) is given by (see Lo (2008)):

$$\boldsymbol{\omega}^* \ = \ \lambda\,\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} \ + \ \xi\,\boldsymbol{\Sigma}^{-1}\boldsymbol{\iota} \tag{19}$$

where λ and ξ are constants defined in Lo (2008). As a consistency check, it is useful to compute the volatility σ of the entire portfolio implied by $\boldsymbol{\omega}^*$:

$$\sigma \ = \ \sqrt{\boldsymbol{\omega}^{*\prime}\boldsymbol{\Sigma}\boldsymbol{\omega}^*} \ . \tag{20}$$

If σ is higher than σ_o, this implies an inconsistency with the following set of objectives:

- target expected return (μ_o)
- desired risk level (σ_o)
- target expected returns and risks of asset classes (μ_i, σ_i)

and at least one of these three objectives must be modified to restore consistency. If the total investment capital is K, the optimal dollar-allocation to each asset class is simply K_i^*

[34]If not, this may be a sign of model misspecification that can serve as a useful diagnostic for identifying potential problems with the portfolio construction process. Alternatively, recent innovations in structured products do allow the synthetic shorting of certain hedge-fund strategies, in which case, more efficient fund-of-funds portfolios may be possible. However, given the complexities of over-the-counter derivatives on hedge funds and the significant risks they can generate, the shorting hedge funds should be contemplated only by the most sophisticated and well-capitalized investors.

where:

$$K_i^* \;=\; \omega_i^* \, K \tag{21}$$

Once the category asset allocations, $\{K_i^*\}$, have been determined, the next step is to decide how to allocate each K_i^* across individual managers within each category i. Although a similar mean-variance optimization may be performed at this stage, the target expected returns, variances, and correlations among individual managers are much harder to estimate precisely. Therefore, the impact of estimation error may outweigh the gains from optimization methods at this level.

An alternative is to begin with identical allocations, K_i^*/m_i, across all m_i managers in category i that satisfy certain minimum conditions, e.g., assets under management, years of experience, track record, etc. Then for each manager, construct a score, S_{ik}, by evaluating the manager against the following criteria, perhaps using a numerical score from 1 to 5 for each criterion:

- anticipated alpha
- anticipated risk
- anticipated capacity
- anticipated correlation with other managers and asset classes
- trading experience and past performance
- backtest performance attribution
- tracking error
- risk controls
- risk transparency
- alpha transparency
- operational risks
- social impact
- other qualitative characteristics

For example, a manager with a high anticipated alpha—as determined through the largely qualitative manager-selection and due-diligence processes—would receive a score of 5, and a manager with a low anticipated alpha would receive a score of 1. Similarly, a high-risk manager (relative to the asset-class volatility, σ_i) would receive a score of 1 and a moderate-risk manager would receive a score of 3. The sum of each of these ratings yields the manager's score, S_{ik}. Then define the relative score, s_{ik}, as:

$$s_{ik} \quad = \quad \frac{S_{ik}}{S_{i1} + \cdots + S_{im_i}} \; . \tag{22}$$

These scores are given equal weighting in (22) but can easily be assigned unique weights to over- or under-emphasize specific attributes. The manager's allocation can then be defined as:

$$\gamma_{ik} \quad = \quad (1-\delta) \times \frac{1}{m_i} \; + \; \delta \times s_{ik} \tag{23}$$

where δ is a parameter that determines the weight placed on the relative score (22) vs. equal-weighting.

For a given set of manager allocations, $\boldsymbol{\gamma}_i \equiv [\; \gamma_{i1} \;\; \cdots \;\; \gamma_{im_i} \;]'$, in asset class i, the implied expected return and volatility of the asset class are given by:

$$\tilde{\mu}_i \quad = \quad \boldsymbol{\gamma}_i' \boldsymbol{\nu}_i \qquad , \qquad \tilde{\sigma}_i \quad = \quad \sqrt{\boldsymbol{\gamma}_i' \boldsymbol{\Sigma}_i \boldsymbol{\gamma}_i} \tag{24}$$

where $\boldsymbol{\nu}_i$ is the vector of expected returns of each manager in asset class i (as determined either by backtests or historical performance), and $\boldsymbol{\Sigma}_i$ is the covariance matrix of the managers in asset class i. Before implementing the allocation $\boldsymbol{\gamma}_i$, it is important to check whether the implied expected return and risk of $\boldsymbol{\gamma}_i$ given in (24) is consistent with the target expected return and risk, μ_i and σ_i, for sector i. If not, then the allocations in $\boldsymbol{\gamma}_i$ may need to be adjusted, or the target expected return and risk must be adjusted to reduce the discrepancy.

Given an allocation $\boldsymbol{\gamma}_i$, each manager's dollar allocation is then:

$$K^*_{ik} \quad = \quad K^*_i \times \gamma_{ik} \; . \tag{25}$$

These scores should be recomputed at least quarterly, and possibly more frequently as changes in market conditions might dictate. Each manager should be given his/her score so that the manager is aware of the link between performance (as determined by the many dimensions of the score) and capital allocation. Moreover, such scores can be used as a hurdle for evaluating new managers, so that the process of manager selection is less arbitrary over time and across individual fund analysts.

The last step in QQIP is to monitor the performance of each manager regularly to ensure that risk budgets and investment mandates are being maintained, and that managers are not straying from their stated styles. For example, if the target risk of asset class i is σ_i, then the realized volatility, $\hat{\sigma}_i$, of the asset class can be compared to σ_i to determine any discrepancies that require further investigation, where:

$$\hat{\sigma}_i \equiv \sqrt{\boldsymbol{\gamma}_i' \boldsymbol{\Sigma}_i \boldsymbol{\gamma}_i} \tag{26}$$

and $\boldsymbol{\Sigma}_i$ is the estimated covariance matrix of the m_i managers in asset class i. Those managers that contribute more than proportionally to the asset-class volatility $\hat{\sigma}_i$ may be required to accept lower capital allocations, and vice versa, other things equal. As performance varies and as parameters change, the allocations across asset classes and across managers will require periodic updating. Allocations should be recomputed monthly, although no action is needed unless the updated allocations are significantly different from the current allocations.

The scope of QQIP can be broadened to include other alternative investments such as venture capital, private equity, and impact investments. However, in such cases, a mean-variance objective function is likely to be inadequate for capturing the investment characteristics of these asset classes. In particular, both venture capital and private equity contain significant illiquidity premia given the nature of those investments, and also involve longer holding periods, hence the mean-variance-liquidity objective function described in Section 5.4 and depicted in Figure 3 may be more appropriate. For impact investments such as environment-related technologies, socially responsible companies, and venture philanthropy, additional metrics that measure impact must be incorporated into the objective function along with risk and expected return. Once such metrics are constructed, the framework of QQIP can be applied to the augmented objective function.

QQIP is considerably more intricate than the straightforward construction of a typical long-only large-cap U.S. equity portfolio, but the intricacies are a manifestation of the greater complexities of alternative investments, and the fact that qualitative judgment still plays a significant role in this endeavor. Nevertheless, the industry is changing rapidly and the hedge-fund investment process is becoming more systematic across all investors. Supporting this trend are various innovations in academic research, new and improved hedge-fund data sources, more sophisticated software applications for hedge-fund portfolio construction and risk management, and professional organizations such as the Alternative Investment Management Association (AIMA), the Managed Funds Association (MFA), and the Chartered Alternative Investment Analysts (CAIA) Association and CAIA certification. These innovations parallel the shift in the mutual fund industry during the 1970s and 1980s toward greater transparency, lower fees, and a more disciplined investment framework, all of which has contributed to the growth and success of the entire industry.

8.5 The Adaptive Markets Hypothesis

One of the most enduring challenges to the very existence of the hedge-fund industry is the Efficient Markets Hypothesis (EMH), the idea that market prices fully reflect all available information. If the EMH holds, how can hedge funds earn "excess" expected returns over time? The answer to this question is not just of academic interest—it has consequences for how investors should allocate their capital across traditional and alternative assets, and how they and regulators should respond to the rapid growth of the hedge-fund industry.

One possible answer is that the EMH is false and hedge funds routinely exploit the departures from efficiency. However, this explanation does not account for the high failure rate in the hedge-fund industry, the capacity constraints that the most successful funds face, and the occasional periods of significant underperformance experienced by the entire industry in comparison to passive buy-and-hold investments. By all accounts, it is very difficult to produce excess risk-adjusted returns consistently and for large pools of assets.

The other extreme is that the EMH is true and hedge funds are simply taking on additional sources of risk that have positive risk premia associated with them. There is some empirical evidence for this view based on estimates of linear factor models for hedge fund returns in which liquidity, credit, and volatility are statistically significant factors driving industry returns (see Section 6). However, there are a number of inordinately successful managers that earn positive risk-adjusted returns even after controlling for such factors, including industry icons such as Warren Buffett, Paul Tudor Jones, Julian Robertson, David Shaw, James Simons, George Soros, and others. It is difficult to dismiss all of these individuals as statistical flukes.

The theoretical foundations of the hedge-fund industry can be found in the work of Sandy Grossman, a successful hedge-fund manager in his own right. In Grossman (1976) and Grossman and Stiglitz (1980), he and Nobel-prize-winning economist Joseph Stiglitz argue convincingly that perfectly informationally efficient markets are an impossibility. If markets are perfectly efficient, there is no profit to gathering information, in which case there would be little reason to trade and markets would not exhibit the volume they currently do. Alternatively, market efficiency is not a binary state but rather a continuum; the *degree* of market inefficiency determines the effort investors will expend to gather and trade on information. Therefore, a non-degenerate market equilibrium occurs only when there are sufficient profit opportunities, i.e., inefficiencies, to compensate investors for the costs of trading and information-gathering. The profits earned by these industrious investors are not free lunches, but the “economic rents” that accrue to those willing to engage in such activities.

Who are the providers of these rents? Black (1986) provides a compelling answer: “noise traders”, individuals who trade for non-informational reasons such as liquidity needs, portfolio rebalancing trades, or random misinformation.

More broadly, the conflict between the EMH and the hedge-fund industry can be reconciled by acknowledging that, like any other industry, value-added is created through innovation and eventually commoditized and depleted through competition. For example, the first mobile device that allowed users to exchange emails remotely—the Blackberry by Research In Motion (RIM)—generated enormous shareholder value for its owners. The returns that accrued to RIM’s original investors are unlikely to be explained by any set of risk factors, especially since the mobile communications industry was just emerging, thanks in no small part to the market that RIM created. Since then, this industry has matured and several competitors to the Blackberry have captured significant market share, including the Apple iPhone and other Android smartphones. The recent returns to RIM investors have been disappointing, not because of changes in factor risk premia, but because competition has reduced RIM’s customer base and RIM has not yet fully adapted to current market conditions.

The dynamics of industrial organization and competition can easily explain the rise and fall of corporations—the same principles apply to hedge-fund strategies and funds. The waxing and waning and re-emergence of various hedge-fund styles are simply manifestations of Schumpeter’s (1939) “creative destruction”, an observation that led Lo (2012) to call the hedge-fund industry the “Galapagos Islands of the financial sector”.[35] By appealing to the principles of evolution—innovation, adaptation, competition, and natural selection—Lo (2004, 2005, 2012, 2015) develops an alternative to the EMH which he calls the Adaptive Markets Hypothesis (AMH). The AMH provides a natural and internally consistent reconciliation of the apparent contradiction between the EMH and the existence and profitability of hedge funds. From the AMH perspective, the EMH is not wrong; it is simply incomplete. Prices reflect as much information as is available from the combination of environmental conditions and the number and nature of “species” in the economy or, to use the appropriate biological term, the market *ecology*. By species, Lo is referring to distinct groups of mar-

[35]Other evolutionary models of financial markets include: Blume and Easley (1992), Luo (1995, 1998, 2001, 2003), Farmer and Lo (1999), Farmer (2002), Hirshleifer and Luo (2001), Kogan, Ross, Wang, and Westerfield (2006), and Brennan and Lo (2011).

ket participants, each behaving in a common manner. For example, pension funds may be considered one species; mutual funds, another; broker/dealers, a third; and hedge-fund managers, a fourth. If multiple species—or the members of a single highly populous species—are competing for scarce resources within a single market, that market is likely to become highly efficient, e.g., the market for S&P 500 futures contracts. If, on the other hand, a small number of species are competing for rather abundant resources in a given market, that market is likely to be less efficient, e.g., the market for pre-Columbian artifacts. Market efficiency is highly context-dependent and dynamic, in much the same way that animal populations advance and decline as a function of the seasons, the number of predators and prey they face, and their abilities to adapt to an ever-changing environment.

The profit opportunities in any given market are akin to the amount of food and water in a particular local ecology—the more resources present, the less fierce the competition. As competition increases, either because of dwindling food supplies or an increase in the animal population, resources are depleted which, in turn, causes a population decline eventually, decreasing the level of competition and starting the cycle again. In some cases, cycles converge to corner solutions, i.e., certain species become extinct, food sources are permanently exhausted, or environmental conditions shift dramatically. By viewing economic profits as the ultimate food source on which market participants depend for their survival, the dynamics of market interactions and financial innovation can be readily derived. From this perspective, the hedge-fund industry is the Galapagos Islands of the financial system—evolutionary dynamics can be seen by the naked eye through the waxing and waning of investment strategies and the birth and death of hedge funds across the various categories. And in the same way that an extinction event for one species can generate ripple effects that have devastating consequences for many other species, extreme losses in the hedge-fund industry can serve as early warning signs of far greater dislocation in the financial ecosystem (see Section 7.1).

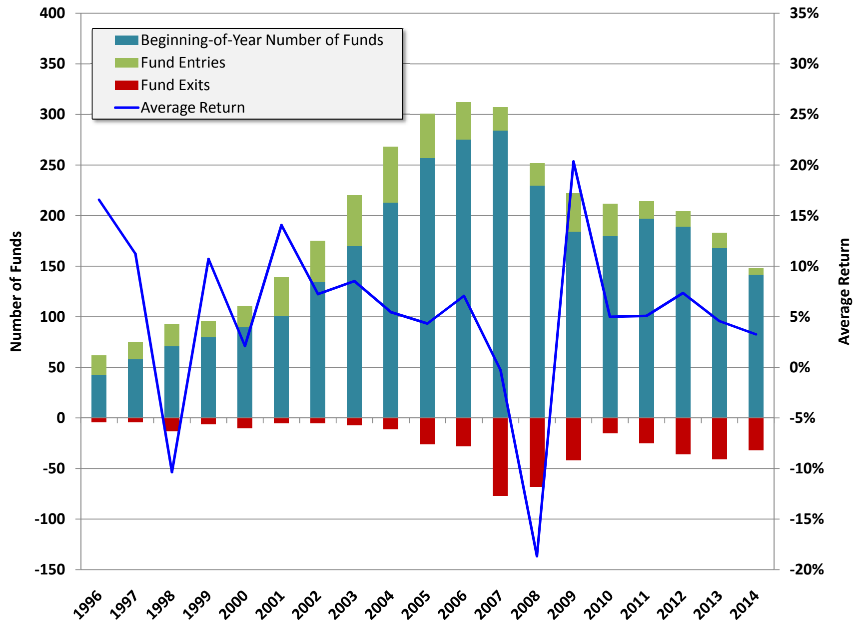
Under the AMH, there is no contradiction between the competitiveness of the financial industry and the possibility that market dislocation can occur and, as a result, certain hedge funds can earn extraordinary profits. During the Fall of 1998, the desire for liquidity and safety by a certain population of investors overwhelmed the population of hedge funds attempting to arbitrage such preferences, causing those arbitrage relations to break down. However, in the years prior to August 1998, fixed-income relative-value traders profited handsomely from these activities, presumably at the expense of individuals with seemingly "irrational" preferences. In fact, such preferences were shaped by a certain set of evolutionary forces, and might be quite rational in other contexts.

Therefore, under the AMH, investment strategies undergo cycles of profitability and loss in response to changing business conditions, the number of competitors entering and exiting the industry, and the type and magnitude of profit opportunities available. As opportunities shift, so too will the affected populations. For example, after 1998, the number of fixed-income relative-value hedge funds declined dramatically—because of outright failures, investor redemptions, and fewer startups in this sector—but many reappeared in subsequent years as performance for this type of investment strategy improved, until the Financial Crisis of 2007–2009.

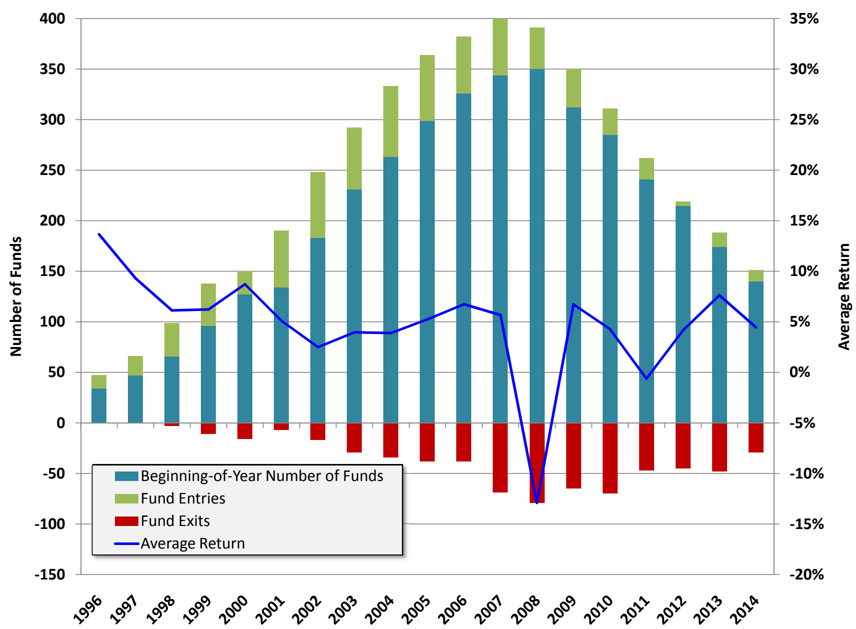
Empirical support for the AMH as it applies to the hedge-fund industry can be found in the dynamics of hedge-fund births and deaths, documented in Section 3.3. Hedge-fund strategies and funds wax and wane in response to risk and reward, as Table 3 clearly shows. A more specific illustration is contained in Figure 9, which depicts the entries, exits, and average annual returns for funds in two particularly dynamic hedge-fund categories, fixed-income arbitrage and equity market neutral. Figure 9a shows that the 1998 rout in fixed-income arbitrage caused a slight increase in the number of funds exiting this category, but its annual returns recovered quickly and the total number of fixed-income-arbitrage funds continued to climb until the Financial Crisis of 2007–2009. However, even before the crisis hit, as the average annual return of fixed-income arbitrage trended downward from 2001 to 2006, the number of exits climbed. Beginning in 2007, the widespread liquidity problems of the crisis caused returns to drop precipitously, along with an unprecedented exodus of capital and hedge funds from fixed-income arbitrage, after which returns improved once more.

Figure 9b offers a somewhat different narrative for equity market neutral hedge funds, whose pre-crisis annual returns were more stable than those of fixed-income arbitrage. This stability contributed to the popularity of this category, also known as "statistical arbitrage", which grew rapidly until its peak in 2007. However, the Quant Meltdown of August 2007 caught many investors and managers by surprise (see Section 7.1), and led to a large number of hedge-fund exits and capital flight from this category post-crisis. Returns are recovering and there are signs that this category is waxing again, however, the changing technological and regulatory landscape of equity markets have greatly increased the complexity of the environment in which equity market neutral hedge funds operate.

The AMH has a number of concrete implications for the hedge-fund industry. The first implication is that contrary to the classical EMH, arbitrage opportunities do exist from time to time in the AMH, as Grossman and Stiglitz (1980) have argued. From an evolutionary perspective, the existence of active liquid financial markets implies that profit opportunities must be present. As they are exploited, they disappear. But new opportunities are also continually being created as certain species die out, as others are born, and as institutions and business conditions change. Rather than the inexorable trend towards higher efficiency predicted by the EMH, the AMH implies considerably more complex market dynamics, with



(a) Fixed-Income Arbitrage



(b) Equity Market Neutral

Figure 9: Fund entries, exits, and average annual returns for single-manager funds in the CS/DJ database from 1996 through 2014 for two categories: (a) Fixed-Income Arbitrage; and (b) Equity Market Neutral.

cycles as well as trends, and panics, manias, bubbles, crashes, and other phenomena that are routinely witnessed in natural market ecologies. These dynamics provide the motivation for active management as Bernstein (1998) suggests, also giving rise to Niederhoffer's (1998) "carnivores" and "decomposers".

A second implication—highlighted by the entry-and-exit dynamics noted in Section 3.3 and Figure 9—is that investment strategies will also wax and wane, performing well in certain environments and performing poorly in other environments. Contrary to the classical EMH in which arbitrage opportunities are competed away, eventually eliminating the profitability of the strategy designed to exploit the arbitrage, the AMH implies that such strategies may decline for a time, and then return to profitability when environmental conditions become more conducive to such trades. An obvious example is risk arbitrage, which has been unprofitable for several years because of the decline in investment banking activity since 2001. However, as mergers and acquisitions activity begins to pick up again, risk arbitrage will start to regain its popularity among both investors and portfolio managers, as it has recently.

A more striking example is autocorrelation in U.S. stock returns. As a measure of market efficiency (recall that the Random Walk Hypothesis implies that returns are serially uncorrelated), autocorrelations of the CRSP value-weighted equity returns index might be expected to take on larger values during the early part of the sample and become progressively smaller during recent years as the U.S. equity market becomes more efficient. Figure 10 displays the statistical significance of the first five autocorrelations of 500-day rolling windows of daily CRSP value-weighted returns according to the Ljung-Box Q-statistic.[36] There are clearly extended periods where autocorrelation is statistically significant such as the 1950s, the 1970s, and the past five years. The *degree* of efficiency—as measured by the first five autocorrelations—varies through time in a cyclical fashion, and there are periods in the 1960s where the market is apparently more efficient than now!

Such cycles are not ruled out by the EMH in theory, but in practice, none of its existing empirical implementations have incorporated these dynamics, assuming instead a stationary

[36]To obtain a summary measure of the overall statistical significance of the autocorrelations, Ljung and Box (1978) propose the following test statistic:

$$Q \;=\; T(T+2)\sum_{k=1}^{p}\hat{\rho}_k^2/(T-k) \tag{27}$$

which is asymptotically χ_p^2 under the null hypothesis of no autocorrelation (see Kendall, Stuart and Ord (1983, Chapter 50.13) for details). By forming the sum of squared autocorrelations, Q reflects the absolute magnitudes of the $\hat{\rho}_k$'s irrespective of their signs, hence time series with large positive or negative autocorrelation coefficients will exhibit large Q-statistics.

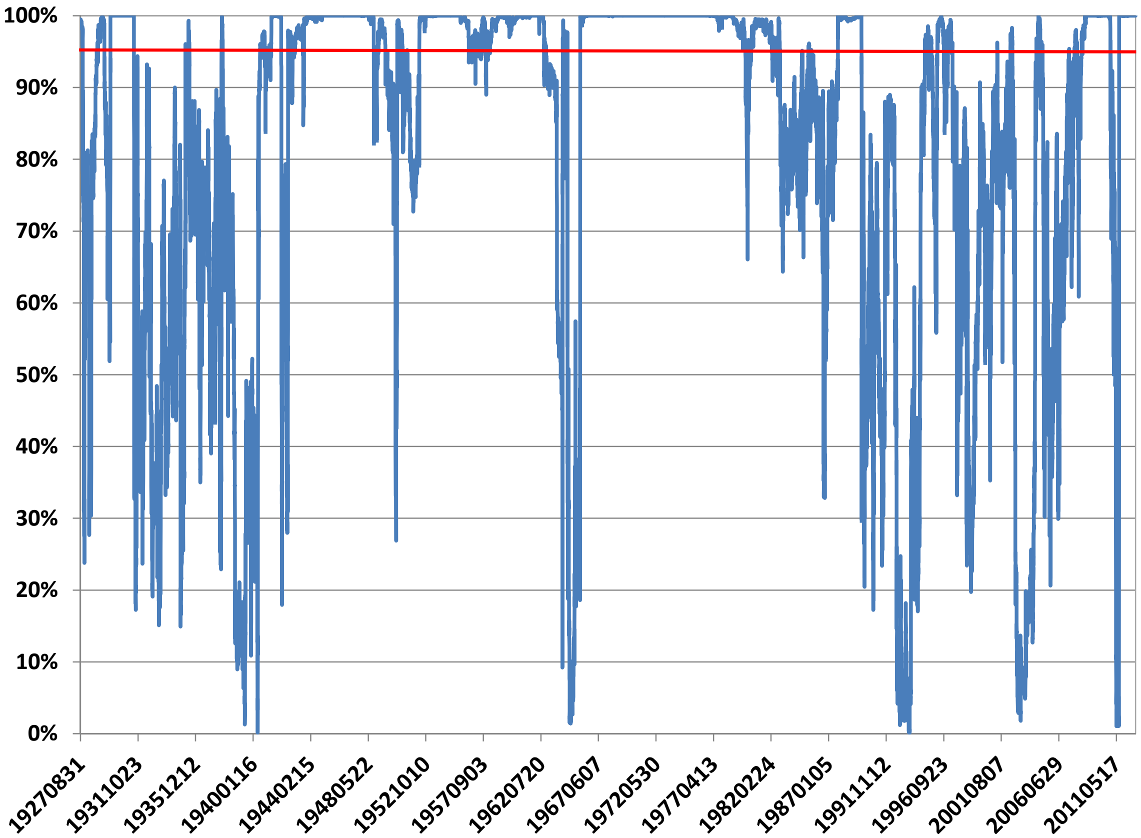


Figure 10: 500-day rolling-window statistical significance ($1-p$-value) of the Ljung-Box Q-statistic for autocorrelation in daily CRSP Value-Weighted Index returns using the first five autocorrelation coefficients, from August 31, 1927 through December 31, 2014. The red line denotes 95% significance, hence all realizations above this line are significant at the 5% level.

world in which markets are perpetually in equilibrium. This widening gulf between the stationary EMH and obvious shifts in market conditions have no doubt contributed to the recent spate of new investment offerings including risk-parity funds, tactical asset allocation funds, and various active ETFs.

A third implication is that innovation is the key to survival. The classical EMH suggests that certain levels of expected returns can be achieved simply by bearing a sufficient degree of risk. The AMH implies that the risk/reward relation varies through time, and that a better way of achieving a consistent level of expected returns is to adapt to changing market conditions. By evolving a multiplicity of capabilities that are suited to a variety of environmental conditions, investment managers are less likely to become extinct as a result of rapid changes in business conditions. Consider the current theory of the demise of the dinosaurs (Alvarez, 1997), and ask where the next financial asteroid might come from.

Finally, the AMH has a clear implication for all financial market participants: survival is the *only* objective that matters in the long run. While profit maximization, utility maximization, and general equilibrium are certainly relevant aspects of market ecology, the organizing principle in determining the evolution of markets and financial technology is simply survival.

These evolutionary underpinnings are more than simple speculation in the context of the hedge-fund industry. The extraordinary degree of competitiveness of global financial markets, the outsize rewards that accrue to the "fittest" managers, and the relatively low barriers to entry and minimal fixed costs of setup suggest that Darwinian selection—"survival of the richest", to be precise—is at work in determining the typical profile of the successful hedge fund. After all, unsuccessful managers are rather quickly eliminated from the population after suffering a certain level of losses, only to be replaced by many eager professionals hoping to make their own name in this dynamic industry. In the same spirit in which the evolutionary biologist Theodosius Dobzhansky (1973) observed that "nothing in biology makes sense except in the light of evolution", none of the dynamics of the hedge-fund industry make sense except in the light of adaptive markets.

9 Conclusion

Two dangerous myths about hedge funds can mislead investors, portfolios, regulators, and policymakers into making inappropriate decisions. The first myth is that all hedge funds are alike, implying that alternative investments comprise a homogeneous asset class that have similar investment characteristics with returns that move in concert. The second myth is that all hedge funds are unique, implying no commonalities and, therefore, no implications for diversification or systemic risk. In this review article, we hope to have dispelled both these myths by reviewing various aspects of the hedge-fund literature and their implications for all stakeholders in this important and dynamic industry.

The freedom with which hedge funds are allowed to invest their capital gives them unique breadth of coverage as an industry and unique depth of expertise at the individual fund level. However, their unconstrained and varied investment strategies contain non-standard forms of risk including phase-locking behavior, illiquidity, nonlinearities, and operational risks that are poorly captured by conventional metrics. More sophisticated risk models are available, but they require much greater training and experience.

The highly competitive nature of this industry implies rapid innovation and attrition, which can greatly benefit the nimble and risk-tolerant investor, but which can be a source of great stress and financial loss for the naive and inattentive investor. But considering the suitability of the various risk dimensions associated with each hedge-fund investment style along with the potential for generating attractive returns, investors can construct a systematic investment process that incorporates hedge-fund investments into more traditional portfolios.

The adaptiveness of the hedge-fund industry also implies that hedge funds can serve as an invaluable monitoring system for identifying trouble spots throughout the financial system. The Financial Crisis of 2007–2009 left a significant mark on the industry, ending an era of excessive optimism about hedge-fund returns and starting a new era in which the industry is retrenching and re-emphasizing its core competencies under heavy investor scrutiny.

Because the hedge-fund industry will continue to evolve rapidly in response to new challenges and opportunities, continuous monitoring and research will be necessary for investors, regulators, and hedge-fund managers to keep up with these changes, and we hope this survey provides a useful perspective for this task.

A Appendix

A.1 Lipper TASS Fund Category Definitions

The following is a list of Lipper TASS category descriptions, that defines the criteria used by Lipper TASS in assigning funds in their database to one of 11 possible categories:

Convertible Arbitrage This strategy is identified by hedge investing in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.

Dedicated Short Bias Short biased managers take short positions in mostly equities and derivatives. The short bias of a manager's portfolio must be constantly greater than zero to be classified in this category.

Emerging Markets This strategy involves equity or fixed income investing in emerging markets around the world. As many emerging markets do not allow short selling, nor offer viable futures or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.

Equity Market Neutral This investment strategy is designed to exploit equity and/or fixed income market inefficiencies and usually involves being simultaneously long and short matched market portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both.

Event Driven This strategy is defined as 'special situations' investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy or reorganization. There are three popular sub-categories in event-driven strategies: risk (merger) arbitrage, distressed/high yield securities, and Regulation D.

Risk Arbitrage - This strategy is identified by managers investing simultaneously in long and short positions in both companies involved in a merger or acquisitions. Merger arbitrageurs are typically long the stock of the company being acquired and short the stock of the acquirer. The principal risk is deal risk, should the merger or acquisition fail to close.

Distressed Securities - Fund managers invest in the debt, equity or trade claims of companies in financial distress and generally bankrupt. The securities of companies in need of legal action or restructuring to revive financial stability typically trade at substantial discounts to par value and thereby attract investments when managers perceive that a turn-around will materialize.

High Yield - Often called junk bonds, this strategy refers to investing in low-grade fixed-income securities of companies that show significant upside potential. Managers generally buy and hold high yield debt.

Regulation D - This strategy refers to investments in micro and small capitalization public companies that are raising money in private capital markets. Investments usually take the form of a convertible security with an exercise price that floats or is subject to a look-back provision that insulates the investor from a decline in the price of the underlying stock.

Fixed Income Arbitrage Funds that attempt to limit volatility and generate profits from price anomalies between related fixed income securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, United States and non-United States government bond arbitrage, forward yield curve arbitrage and mortgage-backed securities arbitrage. The mortgage-backed market is primarily United States-based and over-the-counter.

Global Macro Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and or events. The portfolios of these funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most funds invest globally in both developed and emerging markets.

Long/Short Equity This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional, such as long/short U.S. or European equity, or sector specific, such as long and short technology or healthcare stocks. Long/short equity funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock funds.

Managed Futures This strategy invests in listed financial and commodity futures markets and currency markets around the world. The managers are usually referred to as Commodity Trading Advisors, or CTAs. Trading disciplines are generally systematic or discretionary. Systematic traders tend to use price and market specific information (often technical) to make trading decisions, while discretionary managers use a judgmental approach.

Multi-Strategy This strategy describes hedge funds that use several strategies within the same pool of assets. Hedge funds can use quantitative and fundamental techniques; strategies that are broadly diversified or narrowly focused on specific sectors, have different levels of net exposure, leverage employed, holding period, market capitalization, and valuation techniques.

Fund of Funds A 'Multi Manager' fund will employ the services of two or more trading advisers or Hedge Funds who will be allocated cash by the Trading Manager to trade on behalf of the fund.

A.2 Cleaning Lipper TASS Data

The objective is to detect likely data-entry errors and remove them so that they do not bias the results. For example, if a return were too large by a factor of 100, this might introduce an unwanted bias into the results. As a first step, we re-compute each monthly return based on the reported net asset values (NAVs) to get a more-precise estimate of the rate of return. When the NAV is missing, we simply use the reported rate of return. Then we reject the following three types of suspicious data: monthly returns less than -100%, monthly returns greater than 200%, and monthly returns that are exactly equal to the previous two months' returns.

Except in the birth-death analysis, we restrict our attention to funds that report monthly. Lipper TASS flags nearly all such funds, and in addition we systematically flag as non-monthly any fund whose returns start and stop more than four times (a characteristic that is inconsistent with steady monthly reporting).

A.3 Glossary

Accredited Investor Accredited (or qualified) investor is defined by Rule 501 of Regulation D under the Securities Act of 1933. Generally it refers to individuals with net worth exceeding $1 million and organizations with net worth exceeding $5 million.

Advance Notice Period Advance notice period is the number of days' notice an investor must provide a hedge fund in advance of the redemption period.

Alpha Alpha captures an active return on an investment. Alpha is measured as the return on an investment less systematic contributions to the return.

Beta A beta measures systematic risk of a stock or portfolio with respect to the market as a whole. Beta is the coefficient produced by a univariate regression.

Carried Interest Carried interest or carry, is a share of the profits of an investment or investment fund that is paid to the investment manager in excess of the amount that the manager contributes to the partnership.

Credit Risk Credit risk is an investor's risk of loss arising from a borrower who does not make payments as promised. Such an event is called a default during which both interest and principal may be lost.

Drawdown The drawdown is the measure of decline from a historical peak in the cumulative profit of a financial trading strategy.

Feeder Fund A feeder fund is an investment fund which does almost all of its investments through a master fund via a master-feeder relationship. The master fund oversees all portfolio investments and trading activity. A feeder fund's structure is commonly used by hedge funds to pool investment capital.

Funds of Funds A fund of funds (FOF) is an investment strategy of holding a portfolio of other investment funds. A fund of funds can invest in funds managed by the same investment company or can invest in external funds.

Gate Provision Gate provision is a restriction placed on a hedge fund limiting the amount of withdrawals from the fund during a redemption period. This provision is agreed upfront between a hedge fund manager and a limited partner. Gates are common when illiquid assets are involved. A hedge fund manager has the right to implement the gate provision. The purpose of gates is to prevent a run on the fund by limiting withdrawals. This run on the fund can be especially exacerbated when illiquid securities are involved.

Hedge Fund A hedge fund is an investment fund that can undertake various investment strategies, is typically open-ended, and is open only to particular types of investors specified by regulators. Hedge fund typically employ a wide array of strategies, can short sell, and employ leverage. Hedge fund tend to invest in various asset classes, implement high and low frequency trading, be long and short, invest in assets and derivatives, and have fundamental and quantitative strategies.

High-Water Mark High-water mark is a loss carry-forward provision applied to the calculation of performance fees of hedge funds. When a fund is subject to a high-water mark provision, it will earn performance fees only on net profits, i.e., profits after losses in previous years have been recovered.

Hurdle Rate A hurdle, in the context of an incentive fee, is a level of return that the fund must beat before it can charge an incentive fee. Hurdle rates are typically set as a percentage or are referenced to an index. A typical index for this purpose might be LIBOR (or an equivalent) or an index reflecting the underlying market in which the fund is investing.

Incentive Fee A performance fee that is charged by investment managers of hedge funds. The fee is calculated as a percentage of the increase in the investment fund's net asset value (NAV), which represents the value of the fund's investments. A typical performance fee charged by hedge funds is 20% of the increase in the NAV of the fund. Typically, hedge funds only charge a performance fee on increases in NAV over the high water mark.

Institutional Investor An institutional investor is an organization that trades securities in large quantities or dollar amounts. Banks, insurance companies, pension funds, hedge funds, investment advisers, and mutual funds are examples of institutional investors. Institutional investors often qualify for preferential treatment and lower commissions.

Lock-up Period Lock-up period is an initial time period during which an investor cannot remove money from a hedge fund. All subsequent investments by an investor are often subject to the lockup period.

Management Fee A management fee is a periodic payment that is paid by fund investors for investment and portfolio management services. In a hedge fund, the management fee is calculated as a percentage of the fund's NAV at the time when the fee becomes payable. Management fees range from 1% to 4% per annum with 2% being the norm/mode.

Mark-to-market Accounting Mark-to-market or fair value accounting refers to accounting for the fair value of an asset or liability based on the current market price of the asset or liability or for similar assets and liabilities.

Margin Buying Margin buying is buying securities with cash borrowed from a broker, using other securities or cash as collateral.

Master-Feeder Master-feeder structure allows asset managers to capture the efficiencies of larger pools of assets while allowing for separate market niches of individual funds. Several small feeder funds contribute to one master fund. To comply with distinct legal systems of different jurisdictions, an offshore feeder and an onshore feeder contribute to the same master portfolio.

Net Asset Value Net asset value (NAV) of a hedge fund is calculated as the total value of the fund's portfolio (its assets) less its accrued liabilities (money owed to lending banks, fees owed to investment managers and service providers, and other liabilities).

Open-ended Hedge funds are typically open-ended, meaning that the fund will periodically accept investments and allow investors to withdraw money from the fund. However, hedge fund managers can choose to be closed to new investment.

Redemption Period Redemption period is the number of days an investor must wait before withdrawing money. Most hedge funds have 45-65 day redemption periods.

Subscription Period Subscription period refers to the time period during which investors sign up and commit capital to a hedge fund, before the actual closing of the purchase.

Two and Twenty Two and twenty refers to a typical hedge fund fee structure, where 2% of assets under management is a fixed fee paid annually, and 20% of annual profits above some hurdle rate is the incentive fee, also paid annually.

Volatility Volatility is captured by the standard deviation of the returns of a financial instrument.

References

Ackermann, C., McEnally, R., and D. Ravenscraft, 1999, "The Performance of Hedge Funds: Risk, Return, and Incentives", *Journal of Finance* 54, 833–874.

Adrian, T., 2007, "Measuring Risk in the Hedge Fund Sector", *Current Issues in Economics and Finance* 13 (3).

Adrian, T., and H. Shin, 2008, "Liquidity, Monetary Policy, and Financial Cycles", *Current Issues in Economics and Finance* 14, Federal Reserve Bank of New York.

Adrian, T. and H.S. Shin, 2010, "Liquidity and Leverage", *Journal of Financial Intermediation* 19, 418–437.

Agarwal, V. and N. Y. Naik, 2000a, "Multi-Period Performance Persistence Analysis of Hedge Funds", *Journal of Financial and Quantitative Analysis* 35, 327–342.

Agarwal, V. and N. Y. Naik, 2000b, "Generalized Style Analysis of Hedge Funds", *Journal of Asset Management* 1, 93–109.

Agarwal, V. and N. Y. Naik, 2000c, "On Taking the Alternative Route: Risks, Rewards, and Performance Persistence of Hedge Funds", *Journal of Alternative Investments* 2, 6–23.

Agarwal, V., Daniel, N. D., and N. Y. Naik, 2002, "Determinants of Money-flow and Risk-taking Behavior in the Hedge Fund Industry", Working Paper, Georgia State University.

Agarwal, V. and N. Y. Naik, 2004, "Risk and Portfolio Decisions Involving Hedge Funds", *Review of Financial Studies* 17, 63–98.

Agarwal, V. and J.R. Kale, 2007, "On the Relative Performance of Multi-Strategy and Funds of Hedge Funds", *Journal of Investment Management* 5 (3), 41–63.

Agarwal, V., Daniel, N. D., and N. Y. Naik, 2009, "Role of Managerial Incentives and Discretion in Hedge Fund Performance", *Journal of Finance* 64, 2221–2256.

Agarwal, V., Daniel, N. D., and N. Y. Naik, 2011, "Do Hedge Funds Manage Their Reported Returns?", *Review of Financial Studies* 24 (10), 3281–3320.

Agarwal, V., Jiang, W. Tang, Y., and B. Yang, 2013, "Uncovering Hedge Fund Skill From The Portfolio Holdings They Hide", *Journal of Finance* 68 (2), 739–783.

Agarwal, V., Aragon, G. and Z. Shi, 2014, "Liquidity Spillovers in Hedge Funds: Evidence From the Holdings of Funds of Hedge Funds", Arizona State University Working Paper.

Agarwal, V., Fos, V. and W. Jiang, 2014, "What Happens "Before the Birth" and "After the Death" of a Hedge Fund", *Bankers, Markets, & Investors* 129, 17–25.

Aggarwal, R.K. and P. Jorion, 2009, “The Risks of Emerging Hedge Fund Managers”, *Journal of Investing* 100–107.

Aggarwal, R.K. and P. Jorion, 2010a, “The Performance of Emerging Hedge Fund Managers”, *Journal of Financial Economics* 96, 238–256.

Aggarwal, R.K. and P. Jorion, 2010b, “Hidden Survivorship in Hedge Fund Returns”, *Financial Analysts Journal* 55, 69–74.

Aiken, A.L., Clifford, C.P., and J. Ellis, 2013, “Out of the Dark: Hedge Fund reporting Biases and Commercial Databases”, *Financial Analysts Journal* 26 (1), 208-243.

Allen, F. and E. Carletti, 2008, “The Role of Liquidity in Financial Crises”, 2008 Jackson Hole Symposium.

Alvarez, W., 1997, *T. Rex and the Crater of Doom.* Princeton, NJ: Princeton University Press.

Amenc, N., Martellini, L., Meyfredi, J, and V. Ziemann, 2010, “Passive Hedge Fund Replication - Beyond the Linear Case”, *European Financial Management* 16, 191–210.

Amihud, Y. and H. Mendelson, 1986, “Asset Pricing and the Bid-Asked Spread”, *Journal of Financial Economics* 17, 223–249.

Amin, G. and H. Kat, 2003, “Hedge Fund Performance 1990-2000: Do the “Money Machines” Really Add Value?”, *Journal of Financial and Quantitative Analysis* 38 (2), 251–274.

Amo, A., Harasty, H., and P. Hillion, 2007, “Diversification Benefits of Funds of Hedge Funds Identifying the Optimal Number of Hedge Funds”, *Journal of Alternative Investments* 10, 10–21.

Ang, A. and G. Bekaert, 2002, “International Asset Allocation With Regime Shifts”, *The Review of Financial Studies* 15, 4, 1137–1187.

Ang, A. and N.P.B. Bollen, 2010, “Locked Up by a Lockup: Valuing Liquidity as a Real Option”, *Financial Management* 39 (3), 1069–1095.

Ang, A. Gorovyy, S., and G.B. van Inwegen, 2011, “Hedge Fund Leverage”, *Journal of Financial Economics* 102, 102–126.

Anson, M.J.P., 2001, “Hedge Fund Incentive Fees and the ‘Free Option”’, *Journal of Alternative Investments* 4, 43–48.

Aragon, G., 2005, “Timing Multiple Markets: Theory and Evidence from Balanced Mutual Funds”, Working Paper, Arizona State University.

Aragon, G., 2007, “Share Restrictions and Asset Pricing: Evidence from the Hedge Fund Industry”, *Journal of Financial Economics* 83, 33–58.

Aragon, G. and J. Qian, 2010, "High-water Marks and Hedge Fund Compensation", Working Paper, Arizona State University.

Aragon, G. and P.E. Strahan, 2012, "Hedge Funds as Liquidity Providers: Evidence From the Lehman Bankruptcy", *Journal of Financial Economics* 103, 570-587.

Aragon, G. and V. Nanda, 2012, "On Tournament Behavior in Hedge Funds: High-water Marks, Fund Liquidation, and Managerial Stake", *Review of Financial Studies* 25, 937–974.

Aragon, G. and J.S. Martin, 2012, "A Unique View of Hedge Fund Derivatives Usage: Safeguard or Speculation", *Journal of Financial Economics* 105, 436–456.

Aragon, G., Liang, B., and H. Park, 2013, "Onshore and Offshore Hedge Funds: Are They Twins?", *Management Science* 60.1: 74-91.

Aragon, G., Hertzel, M., and Z. Shi, 2013, "Why Do Hedge Funds Avoid Disclosure? Evidence from Confidential 13F Filings", *Journal of Financial and Quantitative Analysis* 48, 1499–1518.

Aragon, G. and V. Nanda, 2015, "Strategic Delays and Clustering in Hedge Fund Reported Returns", *Journal of Financial and Quantitative Analysis* Forthcoming.

Asness, C.S., Krail, R., and J.M. Liew, 2001, "Do Hedge Funds Hedge?", *Journal of Portfolio Management* 28, 6–19.

Avramov, D, Kosowski, R., Naik, N., and M. Teo, 2011, "Hedge Funds, Managerial Skill, and Macroeconomic Variables", *Journal of Financial Economics* 99, 672–692.

Azlen, M., 2011, "Hedge Funds Replication: A Blended Approach", Working Paper, Frontier Capital Management LLP.

Bali, T. G., Gokcan, S., and B. Liang, 2007, "Value at Risk and the Cross-Section of Hedge Fund Returns", *Journal of Banking and Finance* 31, 827–856.

Bali, T. G., Brown, S. J., and M. O. Caglayan, 2011, "Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns?", *Journal of Financial Economics* 101, 36–68.

Bali, T. G. Brown, S. J., and M. O. Caglayan, 2012, "Systematic Risk and the Cross-Section of Hedge Fund Returns", *Journal of Financial Economics* 106, 114–131.

Baquero, G., Horst, J.T, and M. Verbeek, 2005, "Survival, Look-Ahead Bias, and the Persistence in Hedge Fund Performance", *Journal of Financial and Quantitative Analysis* 40, 493–517.

Baquero, G. and M. Verbeek, 2009, "A Portrait of Hedge Fund Investors: Flows, Performance and Smart Money", Erasmus University Working Paper.

Baquero, G. and M. Verbeek, 2014, "Hedge Fund Flows and Performance Streaks: How Investors Weight Information", Erasmus University Working Paper.

Bares, P., Gibson, R., and S. Gyger, 2003, "Performance in the Hedge Funds Industry: An Analysis of Short- and Long-term Persistence", *Journal of Alternative Investments*, 25–41.

Bein, D. and B. H. Wander, 2002, "How to Incorporate Hedge Funds and Active Portfolio Management into an Asset Allocation Framework", *Journal of Wealth Management*, Winter, 5(3), 14–19.

Bekaert, Geert, and Campbell R. Harvey, 1995, "Time-Varying World Market Integration", *The Journal of Finance* 50, 2, 403–444.

Ben-David, I., Franzoni, F. and R. Moussawi, 2012, "Hedge Funds Stock Trading during the Financial Crisis of 2007-2009", *Review of Financial Studies* 25, 1, 1–54. 403–444.

Ben-David, I., Franzoni, F., Landier, A. and R. Moussawi, 2013, "Do Hedge Funds Manipulate Stock Prices?", *Journal of Finance* 68, 6, 2383–2434. 403–444.

Berk, J. and R. Green, 2004, "Mutual Fund Flows and Performance in Rational Markets", *Journal of Political Economy* 112, 1269–1295.

Bernstein, P., 1998, *Against the Gods: The Remarkable Story of Risk*. John Wiley & Sons, Inc.

Bertsimas, D., Kogan, L. and A.W. Lo, 2001, "Hedging Derivative Securities and Incomplete Markets: An Epsilon-Arbitrage Approach", *Operations Research* 49, 372–397.

Billio, M., Getmansky, M., Lo, A. and L. Pelizzon, 2012, "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors", *Journal of Financial Economics* 104, 535–559.

Billio, M., Getmansky, M and L. Pelizzon, 2009, "Non-Parametric Analysis of Hedge Fund Returns: New Insights from High Frequency Data", *Journal of Alternative Investments* 12 (1), 21–38.

Billio, M., Getmansky, M. and L. Pelizzon, 2012, "Dynamic Risk Exposures in Hedge Funds", *Computational Statistics & Data Analysis* 56, 3517–3532.

Billio, M., Getmansky, M. and L. Pelizzon, 2013, "Crises and Hedge Fund Risk", UMass Amherst Working Paper.

Billio, M., Frattarolo, L. and L. Pelizzon, 2014, "A Time Varying Performance Evaluation of Hedge Fund Strategies Through Aggregation", *Bankers, Markets & Investors* 129, 38–56.

Bisias, D., Flood, M., Lo, A. and S. Valavanis, 2012, "A Survey of Systemic Risk Analytics", *Annual Review of Financial Economics* 4, 255–296.

Black, F., 1986, "Noise", *Journal of Finance* 41, 529–543.

Black, K., 2006, "Improving Hedge Fund Risk Exposures by Hedging Equity Market Volatility or How the VIX Ate My Kurtosis", *The Journal of Trading* Spring Issue, 6–15.

Blume, L. and D. Easley, 1992, "Evolution and Market Behavior", *Journal of Economic Theory* 58, 9–40.

Bollen, N. P. B. and V. K. Pool, 2008, "Conditional Return Smoothing in the Hedge Fund Industry", *Journal of Financial and Quantitative Analysis* 43, 267–298.

Bollen, N. P. B. and V. K. Pool, 2009, "Do Hedge Fund Managers Misreport Returns? Evidence from the Pooled Distribution", *Journal of Finance* 64, 2257–2288.

Bollen, N. P. B. and V. K. Pool, 2012, "Suspicious Patters in Hedge Fund Returns and the Risk of Fraud", *Review of Financial Studies* 25 (9), 2673–2702.

Bondarenko, O., 2004, "Market Price of Variance Risk and Performance of Hedge Funds", Working Paper, University of Illinois Chicago.

Boyson, N., 2008, "Do Hedge Funds Exhibit Performance Persistence? A New Approach", *Financial Analysts Journal* 64 (6), 15–26.

Boyson, N., Stahel C., and R. Stulz, 2010, "Hedge Fund Contagion and Liquidity Shocks", *Journal of Finance* 65 (5), 1789–1816.

Brennan, T. and A. Lo, 2011, "The Origin of Behavior", *Quarterly Journal of Finance* 1, 55–108.

Brennan, T., Lo, A. W., and T. Nguyen, 2015, "Portfolio Theory", in N. Higham, ed., *The Princeton Companion to Applied Mathematics: Princeton University Press.* Princeton, NJ: Princeton University Press.

Brooks, C. and H. M. Kat, 2002, "The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors", *Journal of Alternative Investments* 5 (2), 26–44.

Brown, S.J., Goetzmann, W.N., Ibbotson, R.G., and S.A. Ross, 1992, "Survivorship Bias in Performance Studies", *Review of Financial Studies* 5, 553–580.

Brown, S.J., Goetzmann, W.N., and R.G. Ibbotson, 1999, "Offshore Hedge Funds: Survival and Performance 1989-1995", *Journal of Business* 72 (1), 91–117.

Brown, S.J., Goetzmann, W.N., and J. Park, 2000, "Hedge Funds and the Asian Currency Crisis", *Journal of Portfolio Management* 26 (4), 95–101.

Brown, S.J., Goetzmann, W.N., and J. Park, 2001, "Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry", *Journal of Finance* 56, 1869–1886.

Brown, S.J., and W.N. Goetzmann, 2003, "Hedge Funds with Style", *Journal of Portfolio Management* 29, 101–112.

Brown, S.J., Goetzmann, W.N., and B. Liang, 2004, "Fees on Fees in Funds of Funds", *Journal of Investment Management* 2, 39–56.

Brown, S. J., Goetzmann, W. N., Liang, B. and C. Schwarz, 2008, "Mandatory Disclosure and Operational Risk: Evidence from Hedge Fund Registration", *Journal of Finance* 63, 2785–2815.

Brown, S.J., Fraser, T., and B. Liang, 2008, "Hedge Fund Due Diligence: A Source of Alpha in a Hedge Fund Portfolio Strategy", *Journal of Investment Management* 6 (4), 23–33.

Brown, S. J., Goetzmann, W. N., Liang, B. and C. Schwarz, 2009, "Estimating Operational Risk for Hedge Funds: The Omega Score", *Financial Analyst Journal* 65, 43–53.

Brown, S. J., Goetzmann, W. N., Liang, B. and C. Schwarz, 2012, "Trust and Delegation", *Journal of Financial Economics* 103 (2), 221–234.

Brown, S. J., Gregoriou, G., and R. Pascalau, 2011, "Diversification of Funds of Hedge Funds: Is it Possible to Overdersify?", *Review of Asset Pricing Studies* 2 (1), 89–110.

Brunnermeier, M. and S. Nagel, 2004, "Hedge Funds and the Technology Bubble", *Journal of Finance* 59, 2013–2040.

Brunnermeier, M. and L.H. Pedersen, 2009, "Market Liquidity and Funding Liquidity", *Review of Financial Studies* 22, 2201–2238.

Brunnermeier, M., 2009, "Deciphering the Liquidity and Credit Crunch 2007-2008", *Journal of Economic Perspectives* 23 (1), 77–100.

Buraschi, A., Kosowksi, R., and F. Trojani, 2015, "When There Is No Place to Hide: Correlation Risk and the Cross-Section of Hedge Funds Returns", *Review of Financial Studies* 27: 581-616.

Cai, L. and B. Liang, 2012a, "On the Dynamics of Hedge Fund Strategies", *Journal of Alternative Investments* 14, 51–68.

Cai, L. and B. Liang, 2012b, "Asset Allocation Dynamics in the Hedge Fund Industry", *Journal of Investment Management* 10, 1–25.

Cao, C., Chen, Y., Liang, B., and A. Lo, 2013, "Can Hedge Funds Time Market Liquidity?", *Journal of Financial Economics* 109 (2), 493–516.

Cao, C., Liang, B., Lo, A. and L. Petrasek, 2014, "Hedge Fund Owndership and Stock Market Efficiency", University of Massachusetts Amherst Working Paper.

Capocci, D. and G. Hubner, 2004, "Analysis of Hedge Fund Performance", *Journal of Empirical Finance* 11, 55–89.

Carpenter, J. and A. Lynch, 1999, "Survivorship Bias and Attrition Effects in Measures of Performance Persistence", *Journal of Financial Economics* 54, 337–374.

Cassar, G. and J. Gerakos, 2011, "Hedge Funds: Pricing Controls and the Smoothing of Self-reported Returns", *Review of Financial Studies* 24, 1698–1734.

Cave, A., Hubner, G., and D. Sougne, 2012, “The Market Timing Skills of Hedge Funds during the Financial Crisis”, *Managerial Finance* 38, 4–26.

Chan, N., Getmansky, M., Haas, S., and A. Lo, 2004, “Systemic Risk and Hedge Funds”, presentation at NBER Conference on the Risks of Financial Institutions, October 22–23.

Chan, N., Getmansky, M., Haas, S., and A. Lo, 2006, “Do Hedge Funds Increase Systemic Risk?”, *Federal Reserve Bank of Atlanta Economic Review* Q4, 49–80.

Chan, N., Getmansky, M., Haas, S., and A. Lo, 2007, “Systemic Risk and Hedge Funds”, in M. Carey and R. Stulz, eds., *The Risks of Financial Institutions and the Financial Sector*. Chicago, IL: University of Chicago Press.

Chan, L. K. C, Jegadeesh, N. and Lakonishok, J., 1996, “Momentum Strategies”, *The Journal of Finance* 51, 1681–1713.

Chen, Y., 2007, “Timing Ability in the Focus Market of Hedge Funds”, *Journal of Investment Management* 5, 66–98.

Chen, Y. and B. Liang, 2007, “Do Market Timing Hedge Funds Time the Market”, *Journal of Financial and Quantitative Analysis* 42, 827–856.

Chen, Y., 2011, “Derivatives Use and Risk Taking: Evidence from the Hedge Fund Industry”, *Journal of Financial and Quantitative Analysis* 46 (4), 1073–1106.

Chung, S., Rosenberg, M. and J. F. Tomeo, 2004, “Hedge Fund of Fund Allocations Using a Convergent and Divergent Strategy Approach”, *Journal of Alternative Investments* Summer, 7(1), 44–53.

Cici, G., Kempf, A., and A. Puetz, 2015, “Caught in the Act: How Hedge Funds Manipulate Their Equity Positions”, *Journal of Financial and Quantitative Analysis* Forthcoming.

Clark, K. A. and K. D. Winkelmann, 2004, “Active Risk Budgeting in Action: Understanding Hedge Fund Performance”, *Journal of Alternative Investments*, Winter, 7(3), 35–46.

CRMPG-II (Counterparty Risk Management Policy Group II), 2005, *Toward Greater Financial Stability: A Private Sector Perspective*. July 27. Accessed on July 26, 2015 at
`http://www.crmpolicygroup.org/crmpg2/`.

Cumming, D., Dai, N., and H. Shawky, 2012, “Diversification in the Hedge Fund Industry”, *Journal of Corporate Finance* 18, 166–178.

Diez de los Rios, A. and Garcia, R., 2011, “Assessing and Valuing the Nonlinear Structure of Hedge Fund Returns”, *Journal of Applied Econometrics* 26 (2), 193–212.

Dobzhansky, T., 1973, “Nothing in Biology Makes Sense Except in the Light of Evolution”, *American Biology Teacher* 35, 125–129.

Edelman, D., Fung, W. and D. Hsieh, 2013, "Exploring Uncharted Territories of the Hedge Fund Industry: Empirical Characteristics of Mega Hedge Fund Firms", *Journal of Financial Economics* 109, 734–748.

Edwards, F. R. and M. O. Caglayan, 2001, "Hedge Fund Performance and Manager Skill", *Journal of Futures Markets* 21, 1003–1028.

Eichengreen, B., Mathieson, D, Sharma, S., Chadha, B., Kodres, L. and A. Jansen, 1998, "Hedge Funds and Financial Market Dynamics", International Monetary Fund Occasional Paper No. 166. Washington, DC: International Monetary Fund.

Farmer, D., 2002, "Market Force, Ecology and Evolution", *Industrial and Corporate Change* 11, 895–953.

Farmer, D. and A. Lo, 1999, "Frontiers of Finance: Evolution and Efficient Markets", *Proceedings of the National Academy of Sciences* 96, 9991–9992.

FCIC (Financial Crisis Inquiry Commission), 2011, The Financial Crisis Inquiry Report.

Feffer, S. and C. Kundro, 2003, "Understanding and Mitigating Operational Risk in Hedge Fund Investments", Working Paper, The Capital Markets Company Ltd.

Feng, S., Getmansky, M., and N. Kapadia, 2013, "Flows: The "Invisible Hands" on Hedge Fund Management", Working Paper, University of Massachusetts, Amherst.

Fung, H., Xu, X.E., and J. Yau, 2002, "Global Hedge Funds: Risk, Return, and Market Timing", *Financial Analysts Journal* 19–30.

Fung, W. and D. A. Hsieh, 1997, "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds", *Review of Financial Studies* 10, 275–302.

Fung, W. and D. A. Hsieh, 2000, "Performance Characteristics of Hedge Funds and CTA Funds: Natural Versus Spurious Biases", *Journal of Financial and Quantitative Analysis* 35, 291–307.

Fung, W. and D. A. Hsieh, 2001, "The Risk in Hedge Fund Strategies: Theory and Evidence From Trend Followers", *Review of Financial Studies* 14, 313–341.

Fung, W. and D. A. Hsieh, 2002, "Asset-Based Style Factors for Hedge Funds", *Financial Analysts Journal* 58 (5), 16–27.

Fung, W. and D. A. Hsieh, 2004, "Hedge Fund Benchmarks: A Risk-Based Approach", *Financial Analysts Journal* 60, 65–80.

Fung, W. Hsieh, D.A., Naik, N., and T. Ramadorai, 2008, "Hedge Funds, Performance, Risk, and Capital Formation", *Journal of Finance* 63, 1777–1803.

Gao, M. and J. Huang, 2014, "Capitalizing on Capitol Hill: Informed Trading by Hedge Fund Managers", AFA 2012 Chicago Meetings Paper.

Gao, G.P., Gao, P., and Z. Song, 2014, "Do Hedge Funds Exploit Rare Disaster Concerns?", Cornell University Working Paper.

Getmansky, M., Lo, A.W., and S.X. Mei, 2004, "Sifting Through the Wreckage: Lessons from Recent Hedge-Fund Liquidations", *Journal of Investment Management* 2 (4), 6–38.

Getmansky, M., Lo, A., and I. Makarov, 2004, "An Econometric Model of Serial Correlation and Illiquidity of Hedge Fund Returns", *Journal of Financial Economics* 74, 529–610.

Getmansky, M., Liang, B., Schwarz, C., and R. Wermers, 2015, "Share Restrictions and Investor Flows in the Hedge Fund Industry", Working Paper, University of Massachusetts, Amherst.

Getmansky, M., 2012, "The Life Cycle of Hedge Funds: Fund Flows, Size and Performance", *Quarterly Journal of Finance* 2 (2), 1–53.

Geczy, C., 2014, "The New Diversification: Open Your Eyes to Alternatives", *The Journal of Portfolio Management* Special 40th Anniversary Issue, 146–155.

Gimein, M., 2005, "Is a Hedge Fund Shakeout Coming Soon? This Insider Thinks So", *New York Times*, September 4.

Glode, V. and R. C. Green, 2011, "Information Spill-overs and Performance Persistence for Hedge Funds", *Journal of Financial Economics* 101, 1–17.

Glosten, L. and P. Milgrom, 1985, "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders", *Journal of Financial Economics* 13, 71–100.

Goetzmann, W.N., Ingersoll, J.E., and S.A. Ross, 2003, "High-water Marks and Hedge Fund Management Contracts", *Journal of Finance* 58, 1685–1717.

Goldman Sachs & Co. and Financial Risk Management Ltd., 1999, "The Hedge Fund "Industry" and Absolute Return Funds", *The Journal of Alternative Investments* Spring, 1(4), 11–27.

Goldman Sachs Asset Management, 2007, "The Quant Liquidity Crunch", Goldman Sachs Global Quantitative Equity Group, August.

Gorton, G. and A. Metrick, 2012, "Securitized Banking and the Run on Repo", *Journal of Financial Economics* 104, 425–451.

Griffin, J. and J. Xu, 2009, "How Smart are the Smart Guys? A Unique View From Hedge Fund Stock Holdings", *Review of Financial Studies* 22, 2331–2370.

Grossman, S., 1976, "On The Efficiency of Competitive Stock Markets Where Trades Have Diverse Information", *Journal of Finance* 31, 573–585.

Grossman, S. J. and J. E. Stiglitz, 1980, "On the Impossibility of Informationally Efficient Markets", *American Economic Review* 70 (3), 393–408.

Guidolin, M. and A. Timmermann, 2008, "International Asset Allocation under Regime Switching, Skew and Kurtosis Preferences", *Review of Financial Studies* 21, 889–935.

Gupta, A. and B. Liang, 2005, "Do Hedge Funds Have Enough Capital? A Value at Risk Approach", *Journal of Financial Economics* 77, 219–253.

Gupta, R. and H. Kazemi, 2007, "Factor Exposures and Hedge Fund Operational Risk: The Case of Amaranth", *Alternative Investment Quarterly* 23.

Hasanhodzic, J. and A. Lo, 2006, "Attack of the Clones", *Alpha Magazine*, June/July.

Hasanhodzic, J. and A. Lo, 2007, "Can Hedge-Fund Returns Be Replicated?: The Linear Case", *Journal of Investment Management* 5, 5–45.

Hasanhodzic, J., Lo, A., and P. Patel, 2009, "The CS 130/30 Index: A Summary and Performance Comparison", Credit Suisse White Paper.

Hasbrouck, J. and R. Schwartz, 1988, "Liquidity and Execution Costs in Equity Markets", *Journal of Portfolio Management* 14, 10–16.

Healy, A. and A. Lo, 2009, "Jumping the Gates: Using Beta-Overlay Strategies to Hedge Liquidity Constraints", *Journal of Investment Management* 7(2009), 1–20.

Heuson, A., Hutchinson, M and A. Kumar, 2015, "Assessing Hedge Fund Performance When Fund Returns Are Skewed", University of Miami Working Paper.

Hendricks, D., Patel, J., and R. Zeckhauser, 1997, "The J-Shape of Performance Persistence Given Survivorship Bias", *The Review of Economics and Statistics* 79 (2), 161–166.

Henriksson, R. and R. Merton, 1981, "On Market Timing and Investment Performance: Statistical Procedures for Evaluating Forecasting Skills", *Journal of Business* 54, 513–533.

HFR, 2013, *Global Hedge Fund Industry Report*. Chicago, IL: HFR.

Higham, N., 2002, "Computing the Nearest Correlation Matrix–A Problem from Finance", *IMA J. Numer. Anal.* 22, 329–343.

Hill, J., Nadig, D. and M. Hougan, 2015, "A Comprehensive Guide to Exchange-Traded Funds (ETFs)", CFA Institute Research Foundation.

Hirshleifer, D. and G. Luo, 2001, "On the Survival of Overconfident Traders in a Competitive Securities Market", *Journal of Financial Markets* 4, 73–84.

Hodder, J. and J. Jackwerth, 2007, "Incentive Contracts and Hedge Fund Management", *Journal of Financial and Quantitative Analysis* 42, 811–826.

Horst, J., and M. Verbeek, 2007, "Fund Liquidation, Self-Selection, and Look-Ahead Bias in the Hedge Fund Industry", *Review of Finance* 4, 605–632.

Howell, M., 2001, "Fund Age and Performance", *The Journal of Alternative Investments* 4 (2), 57–60.

Ibbotson, R., Chen, P., and K. Zhu, 2011, "The ABCs of Hedge Funds: Alphas, Betas, and Costs", *Financial Analysts Journal* 67, 15–25.

Ibbotson, R., 2013, *Market Results for Stocks, Bonds, Bills, and Inflation 1926–2012.* Morningstar, Ibbotson SBBI 2013 Classic Yearbook.

Ineichen, A., 2001, "The Myth of Hedge Funds: Are Hedge Funds The Fireflies Ahead of the Storm?", *Journal of Global Financial Markets* 2 (4), 34–46.

Jagannathan, R., Malakhov, A., and D. Novikov, 2010, "Do Hot Hands Exist Among Hedge Fund Managers? An Empirical Evaluation", *Journal of Finance* 65, 217–255.

Jen, P., Heasman, C. and K. Boyatt, 2001, "Alternative Asset Strategies: Early Performance in Hedge Fund Managers", *Lazard Asset Management.*

Joenväärä, J., Kosowski, R., and P. Tolonen, 2014, "Hedge Fund Performance: What Do We Know?", Imperial College Working Paper.

Jiang, H. and B. Kelly, 2012, "Tail Risk and Hedge Fund Returns", University of Chicago Working Paper.

Jorion, P., 2007, "Risk Management for Hedge Funds with Position Information", *Journal of Portfolio Management* 34, 127–134.

Jorion, P., 2008, "Risk Management for Event-Driven Funds", *Financial Analysts Journal* 64, 61–73.

Jorion, P. and C. Schwarz, 2014a, "The Strategic Listing Decisions of Hedge Funds", *Journal of Financial and Quantitative Analysis* 49: 773–796.

Jorion, P. and C. Schwarz, 2014b, "Are Hedge Fund Managers Systematically Misreporting? Or Not?", *Journal of Financial Economics* 111(2), 311–327.

Jylha, P., 2011, "Hedge Fund Return Misreporting: Incentives and Effects", Working Paper, Aalto University.

Kaminski, K., 2011, *In Search of Crisis Alpha: A Short Guide to Investing in Managed Futures.* Chicago, IL: Chicago Mercantile Exchange.

Kao, D., 2002, "Battle for Alphas: Hedge Funds versus Long-Only Portfolios", *Financial Analysts Journal* 58 (2), 16–34.

Kat, H. and F. Menexe, 2003, "Persistence in Hedge Fund Performance: The True Value of a Track Record", *Journal of Alternative Management* 5, 66–72.

Kat, H. and H. Palaro, 2005, "Who Needs Hedge Funds? A Copula-Based Approach to Hedge Fund Return Replication". Working Paper, Cass Business School, City University, London.

Kat, H. and H. Palaro, 2006a, "Replication and Evaluation of Fund of Hedge Funds Returns". Working Paper, Cass Business School, City University, London.

Kat, H. and H. Palaro, 2006b, "Superstars or Average Joes?: A Replication-Based Performance Evaluation of 1917 Individual Hedge Funds". Working Paper, Cass Business School, City University, London.

Kazemi, H., Li, Y., and F. Tu, 2008, "Replication and Benchmarking of Hedge Funds", *Journal of Alternative Management* 11, 40–59.

Kazemi, H. and Y. Li, 2009, "Market Timing of CTAs: An Examination of Systematic and Discretionary CTAs", *Journal of Futures Markets* 29, 1067–1099.

Kendall, S. Stuart, A., and J. Ord, 1983, *The Advanced Theory of Statistics* Vol 3, 4th ed., Griffin, High Wycombe, UK.

Khandani, A. and A. Lo, 2007, "What Happened to the Quants in August 2007", *Journal of Investment Management* 5, 29–78.

Khandani, A. and A. Lo, 2011a, "What Happened to the Quants in August 2007? Evidence from Factors and Transactions Data", *Journal of Financial Markets* 14, 1–46.

Khandani, A. and A. Lo, 2011b, "Illiquidity Premia in Asset Returns: An Empirical Analysis of Hedge Funds, Mutual Funds, and U.S. Equity Portfolios", *Quarterly Journal of Finance* 2, 205–264.

Kogan, L., Ross, S., Wang, J. and M. Westerfield, 2006, "The Price Impact Survival and Survival of Irrational Traders", *Journal of Finance* 61, 195–229.

Kosowski, R., Naik, N., and M. Teo, 2007, "Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis", *Journal of Financial and Quantitative Analysis* 84, 229–264.

Kouwenberg, R. and W. Ziemba, 2007, "Incentives and Risk Taking in Hedge Funds", *Journal of Banking and Finance* 31, 3291–3310.

Kramer, D., 2001, "Hedge Fund Disasters: Avoiding the Next Catastrophe", *Alternative Investment Quarterly* 1.

Kraus, A. and H. Stoll, 1972, "Price Impacts of Block Trading on the New York Stock Exchange", *Journal of Finance* 27, 569–588.

Krishnamurthy, A., 2010, "Amplification Mechanisms in Liquidity Crises", *American Economic Journal: Macroeconomics* 2 (3), 1–30.

Kruttli, M., Patton, A. and T. Ramadorai, 2014, "The Impact of Hedge Funds on Asset Markets", Oxford University Working Paper.

Kyle, A., 1985, "Continuous Auctions and Insider Trading", *Econometrica* 53, 1315–1335.

Lakonishok, J., Shleifer, A., and Vishny, R., 1994, "Contrarian Investment, Extrapolation, and Risk", *The Journal of Finance* 49, 1541–1578.

Learned, M. and F. Lhabitant, 2003, "Hedge Fund Diversification: How Much is Enough?", *Journal of Alternative Investments* 5 (3), 23–49.

Lee, P. and A. Lo, 2014, "Hedge Fund Beta Replication: A Five-Year Retrospective", *Journal of Investment Management* 12, 5–18.

Li, H., Zhang, X, and R. Zhao, 2011, "Investing in Talents: Manager Characteristics and Hedge Fund Performances", *Journal of Financial and Quantitative Analysis* 46, 59–82.

Liang, B., 1999, "On the Performance of Hedge Funds", *Financial Analysts Journal* 55, 72–85.

Liang, B., 2000, "Hedge Fund: The Living and The Dead", *Journal of Financial and Quantitative Analysis* 35, 309–326.

Liang, B., 2001, "Hedge Fund Performance: 1990-1999", *Financial Analysts Journal* 57, 11–18.

Liang, B., 2003, "The Accuracy of Hedge Fund Returns", *Journal of Portfolio Management* 29, 111–122.

Liang, B., 2004, "Alternative Investments: CTAs, Hedge Funds, and Funds of Funds", *Journal of Investment Management* Forth Quarter 2, 76–93.

Liang, B. and H. Park, 2007, "Risk Measures for Hedge Funds: A Cross-Sectional Approach", *European Financial Management*, 333–370.

Liang, B. and H. Park, 2010, "Predicting Hedge Fund Failure: A Comparison of Risk Measures", *Journal of Financial and Quantitative Analysis* 45, 199–222.

Lillo, F., Farmer, D. and R. Mantegna, 2003, "Master Curve for Price-Impact Function", *Nature* 421, 129–130.

Litterman, R., 2013, "The Quant Liquidity Crunch of 2007: An Unrecognized Crowded Trade", S. Donald Sussman Award Lecture, September 17, accessed January 4, 2014. http://18.9.60.50/videos/25938-s-donald-sussman-award-lecture-the-quant-liquidity-crunch-of-2007-an-unrecognized-crowded-trade

Ljung, G. and G. Box, 1978, "On a Measure of a Lack of Fit in Time Series Models", *Biometrika* 65 (2), 297–303.

Lo, A., 1999, "The Three P's of Total Risk Management", *Financial Analysts Journal* 55, 13–26.

Lo, A., 2001, "The Statistics of Sharpe Ratios", *Financial Analysts Journal* 58 (4), 36–52.

Lo, A., 2004, "The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective", *Journal of Portfolio Management* 30, 15–29.

Lo, A., 2005, "Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis", *Journal of Investment Consulting* 7, 21–44.

Lo, A., 2008, *Hedge Funds: An Analytic Perspective*. Princeton, NJ: Princeton University Press.

Lo, A., 2012, "Adaptive Markets and the New World Order, *Financial Analysts Journal* 68, 18–29.

Lo, A., 2015, *The Adaptive Markets Hypothesis*, Clarendon Lectures in Finance, forthcoming. Oxford, UK: Oxford University Press.

Lo, A., Mamaysky, H. and J. Wang, 2004, "Asset Prices and Trading Volume Under Fixed Transaction Costs", *Journal of Political Economy* 112, 1054–1090.

Lo, A. and J. Wang, 2006, "Trading Volume: Implications of an Intertemporal Capital Asset Pricing Model", *Journal of Finance* 61, 2805–2840.

Lo, A. and P. Patel, 2008, "130/30: The New Long-Only", *Journal of Portfolio Management* 34, 12–38.

Lochoff, R., 2002, "Hedge Funds and Hope", *Journal of Portfolio Management* 28 (4), 92–99.

Luo, G., 1995, "Evolution and Market Competition", *Journal of Economic Theory* 67, 223–250.

Luo, G., 1998, "Market Efficiency and Natural Selection in a Commodity Futures Market", *Review of Financial Studies* 11, 647–674.

Luo, G., 2001, "Natural Selection and Market Efficiency in a Futures Market with Random Shocks", *Journal of Futures Markets* 21, 489–516.

Luo, G., 2003, "Evolution, Efficiency and Noise Traders in a One-Sided Auction Market", *Journal of Financial Markets* 6, 163–197.

Malkiel, B. and A. Saha, 2005, "Hedge Funds: Risk and Return", *Financial Analysts Journal* 61, 80–88.

Markowitz, H., 1952, "Portfolio Selection", *Journal of Finance* 7, 77–91.

Merton, R., 1981, "On Market Timing and Investment Performance. An Equilibrium Theory of Value for Market Forecasts", *Journal of Business* 54 (3), 363–406.

Mitchell, M. and T. Pulvino, 2001, "Characteristics of Risk in Risk Arbitrage", *Journal of Finance* 50, 549–572.

Montier, J., 2007, "The Myth of Exogenous Risk and the Recent Quant Problems", Accessed January 4, 2014.
http://behaviouralinvesting.blogspot.com/2007/09/myth-of-exogenous-risk-and-recent-quant.html

Niederhoffer, V., 1998, *The Education of a Speculator*, New York: John Wiley & Sons.

OFR (Office of Financial Research), 2013, *2013 Annual Report*. Washington, DC: Office of Financial Research.

Ozik, G. and R. Sadka, 2014, "Skin in the Game versus Skimming the Game: Governance, Share Restrictions, and Insider Flows", *Journal of Quantitative Analysis* Forthcoming.

Pastor, L. and R. Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns", *Journal of Political Economy*, 642–685.

Panageas, S. and M. Westerfield, 2009, "High-Water Marks: High Risk Appetites? Convex Compensation, Long Horizons, and Portfolio Choice", *Journal of Finance*, 64 (1), 1–36.

Patton, A. and T. Ramadorai, 2013, "On the High-Frequency Dynamics of Hedge Fund Risk Exposures", *Journal of Finance* 68: 597–635.

Patton, A., Ramadorai, T., and M. Streatfield, 2013, "Change You Can Believe In? Hedge Fund Data Revisions", *Journal of Finance* Forthcoming.

Qi, H. and D. Sun, 2006, "A Quadratically Convergent Newton Method for Computing the Nearest Correlation Matrix", *SIAM J. Matrix Anal. Appl.* 28, 360–385.

Rajan, R., 2005, "Has Financial Development Made the World Riskier?", in *The Greenspan Era: Lessons for the Future, A Symposium Sponsored by the Federal Reserve Bank of Kansas City*, August 25–27, Jackson Hole, WY.

Ramadorai, T., 2012, "The Secondary Market for Hedge Funds and the Closed Hedge Fund Premium", *Journal of Finance* 67: 479–512.

Ramadorai, T., 2013, "Capacity Constraints, Investor Information, and Hedge Fund Returns", *Journal of Financial Economics* 107: 401–416.

Reca, B., Sias, R. and H. Turtle, 2013, "Hedge Fund Crowds and Mispricing", University of Arizona Working Paper.

Reinhart, C. and K. Rogoff, 2009, *This Time is Different: Eight Centuries of Financial Folly*. Princeton University Press.

Roncalli, T. and J. Teiletche, 2008, "An Alternative Approach to Alternative Beta", *Journal of Financial Transformation* 24.

Roncalli, T. and G. Weisang, 2010, "Tracking Problems, Hedge Fund Replication, and Alternative Beta", *Journal of Financial Transformation* 31.

Rothman, M., 2007a, "Turbulent Times in Quant Land", U.S. Equity Quantitative Strategies, Lehman Brothers Research.

Rothman, M., 2007b, "View from QuantLand: Where Do We Go Now?" U.S. Equity Quantitative Strategies, Lehman Brothers Research.

Rothman, M., 2007c, "Rebalance of Large Cap Quant Portfolio", U.S. Equity Quantitative Strategies, Lehman Brothers Research.

Sadka, R., 2010, “Liquidity Risk and the Cross-section of Hedge-fund Returns”, *Journal of Financial Economics* 98, 54–71.

Sadka, R., 2012, “Hedge-fund Performance and Liquidity Risk”, *Journal of Investment Management* 10, 60–72.

Schneeweis, T., Spurgin, R., and D. McCarthy, 1996, “Survivor Bias in CTA Performance”, *Journal of Futures Markets* 16 (7).

Schneeweis, T. and R. Spurgin, 1998, “Multi-Factor Analysis of Hedge Fund, Managed Futures, and Mutual Fund Return and Risk Characteristics”, *Journal of Alternative Investments* 1, 1–24.

Schneeweis, T., Kazemi, H. and E. Szado, 2011, “Hedge Fund Database “Deconstruction”: Are Hedge Fund Databases Half Full or Half Empty?”, *Journal of Alternative Investments* 14, 65–88.

Schumpeter, J., 1939, *Business Cycles: A Theoretical, Historical, And Statistical Analysis of the Capitalist Process.* New York: McGraw-Hill.

SEC (U.S. Securities and Exchange Commission), 2013, Annual Staff Report Relating to the Use of Data Collected from Private Fund Systemic Risk Reports.

Shiller, R., 2005, “‘Irrational Exuberance’—Again”, CNN Money, January 25. Accessed January 4, 2014.
http://money.cnn.com/2005/01/13/real_estate/realestate_shiller1_0502/

Stemme, K. and P. Slattery, 2002, “Hedge Fund Investments: Do it Yourself or Hire a Contractor?”, *Journal of Alternative Investments*, Special Issue, 1, 60–68.

Sun, Z., Wang, A., and L. Zheng, 2012, “The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance”, *Review of Financial Studies* 25 (1), 96–143.

Teo, M., 2009, “The Geography of Hedge Funds”, *Review of Financial Studies* 22, 3531–3561.

Teo, M., 2011, “The Liquidity Risk of Liquid Hedge Funds”, *Journal of Financial Economics* 100 (1), 24–44.

Tiniç, S., 1972, “The Economics of Liquidity Services”, *Quarterly Journal of Economics* 86, 79–93.

Titman, S. and C. Tiu, 2011, “Do the Best Hedge Funds Hedge”, *Review of Financial Studies* 24, 123–168.

Treynor, J. and K. Mazuy, 1966, “Can Mutual Funds Outguess the Market”, *Harvard Business Review* 44, 131–136.

Tuchschmid, N., Wallerstein, E. and S. Zaker, 2010, “How Do Hedge Fund Clones Manage the Real World?”, *Journal of Alternative Investments* 12, 37–50.

U.S. Treasury, 2013, “Legacy Securities Public-Private Investment Program Update—Quarter Ended September 30, 2013”, October 28, 2013.

Zask, E., 2000, “Hedge Funds: A Methodology for Hedge Fund Valuation”, *Journal of Alternative Investments*, Winter, 3(3), 43–46.