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The Impact of Leverage on Hedge Fund Performance

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The Impact of Leverage on Hedge Fund Performance

An honors thesis presented to
Department of Finance,
University at Albany, State University of New York
in partial fulfillment of the requirements
for graduation with Honors in Finance
and
graduation from The Honors College

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Research Advisor: David M. Smith, Ph.D.

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Abstract

In this paper, the effect of leverage on hedge fund performance is measured. TASS data from 1994 to 2016 are used to measure the impact of leverage on hedge fund performance. Three hedge fund performance measurements are regressed on degree of leverage with eight control variables including fund size, strategies, and use of derivatives. The results show that for strategy-adjusted return as a performance measurement, hedge fund leverage has a negative impact on fund performance. Also there is evidence of diseconomies of scale where funds with medium-sized assets under management (AUM) tend to show better performance than funds with high AUM. No significant relation between use of leverage and performance is observed for other performance measurements, including the Fung and Hsieh seven and eight-factor alpha and style-adjusted return.

Acknowledgements

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Table of Contents

Abstract	2
Acknowledgements	3
Introduction	5
Literature Review	6
1. Nature of the Hedge Fund Leverage	6
2. Previous Studies	6
3. Performance Measurements	8
Hypotheses	10
Data and Methodology	10
1. Data Description	10
2. Data Biases	17
3. Methodology	17
Empirical Analysis	22
Conclusion	23
References	26

The Impact of Leverage on Hedge Fund Performance

Introduction

Leverage plays a central role in hedge fund management, and likely affects the level of performance and assets under management. Approximately 50% of hedge funds use leverage as of April 2016 while other managed funds such as mutual funds and exchange-traded funds are not permitted to take high leverage. Since the notorious incident involving Long-Term Capital Management L.P. (LTCM) in 1998, hedge fund leverage been accused of increasing systemic risk and adding stresses across the financial system (CGFS (1999)). Although information on the hedge fund leverage use is relatively scarce, it is important to analyze the available data.

There are not many studies regarding the impact of hedge fund leverage, and data used in the previous literature exclude the post-financial crisis timeperiod. In addition, extant studies find significant results on the macroeconomic aspect of leverage, yet less research exists on microeconomic or fund-specific determinants, and the results of the hedge fund leverage are insignificant. It is also time to reconsider performance measurement, because extensive literature has recently developed in that area.

In this paper, the effect of leverage on hedge fund performance is measured. The Lipper TASS database as of 1994 to 2016 is used to measure the impact of leverage on hedge fund performance. The relation between dependent and independent variable is measured with eight control variables that are expected to impact the degree of leverage are considered in this analysis. The results show whether leverage use improves or decreases hedge fund performance across multiple strategies and fund size.

Literature Review

1. Nature of the Hedge Fund Leverage

Leverage is a unique feature of hedge fund culture, unlike other managed investments such as mutual funds and exchange-traded funds. The goal of most hedge funds is to achieve maximum returns with controlled risks. Hedge fund investors can use margin accounts and credit lines to borrow money from a prime broker or a third party with the hope of amplifying gains. Also as the word “hedge” in hedge funds represents, the industry seeks safe investments by using derivatives where the maximum loss is much smaller than the potential gain. From the manager’s perspective, leverage in hedge funds emerges in three major ways: fund managers can simply borrow money, fund managers can deploy short-sales, and fund managers can use derivatives in their portfolios. Due to difficulties in issuing long-term debt and securing long-term borrowing, leverage is mostly obtained through short-term funding. Although the Federal Reserve Board’s Regulation T (Reg T) limits hedge fund leverage to a maximum of 50% of the value of a position on margin, prime brokers allow hedge fund managers to exceed the limits by offering offshore investment vehicles and portfolio margining. For the compensation, prime brokers typically charge a spread over London Interbank Offered Rate (LIBOR) for investors with long position, and pay a spread below LIBOR when investors deposit cash as collateral for short positions.

2. Previous Studies

The macroeconomic characteristics of hedge fund leverage are well described by Ang, Gorovyy, and Inwegen (2011). Ang et al. (2011) use predictive and contemporaneous models to test the factors that encourage or restrict the usage of leverage. Both models are linear regressions that include economy-wide variables and fund-specific variables as major factors that cause

leverage. According to their research, average gross leverage, which is defined as $(\text{Long positions} + \text{Short positions}) / \text{Net Asset Value}$, is 2.1 across all hedge funds. A low result in average gross leverage is because most of hedge funds belong to the equity sector where leverage is low, while some funds with large leverage exceed gross leverage of 30. Also their research observes that hedge fund leverage tends to be counter-cyclical to the market leverage of financial intermediaries. For example, there was a tendency for hedge funds to maintain stable leverage during the financial crisis whereas leverage of investment banks was at its highest. However, the determinants of leverage are observed in macroeconomic aspect, and only fund-specific variable predicting hedge fund leverage was return volatility, where increase in fund return volatility tend to reduce leverage. This result of fund-specific determinant follows the observation of Schneeweis, Martin, Kazemi and Karavas (2005). Since data used for the research exclude the post-financial crisis period, fund-specific variables need further study to reflect the current situation. Furthermore, the research of Ang et al. (2011) data are obtained from large fund-of-hedge-funds, which leaves curiosity whether their sample data are able to represent the population of the hedge fund industry.

Empirical research similar to this paper was previously conducted by Schneeweis et al. (2005). Their research shows a negative relation between leverage usage and return volatility across hedge fund strategies. However, within particular hedge fund strategies, at the fund level, little evidence of systematic relation between leverage use and the risk adjusted performance is found. Although Schneeweis et al. (2005) contribute importantly to the literature, the time horizon of their data needs to be updated, and the performance measurements in their study need to be re-considered. Schneeweis et al. (2005) use the Sharpe (1966) ratio as a performance measurement, while Yau, Schneeweis, Robinson, and Weiss (2007) point out that hedge fund characteristics and reporting conventions tend to distort the Sharpe ratio and make it upwardly biased. Also Ingersoll,

Spiegel, Goetzmann, and Welch (2007) show that derivative instruments may be used to manipulate commonly used performance measurements such as the Sharpe ratio and Jensen's alpha. Chen (2011) observes that 71% of all hedge funds trade derivatives. Combining the ideas of Ingersoll et al. (2007) and Chen (2011) suggests that researchers should use new performance measurement in the hedge fund industry. Advanced performance measurement such as the seven asset-based style (ABS) factor model of Fung and Hsieh (2004) or manipulation-proof performance model (MPPM) of Ingersoll et al. (2007) should be considered for this research.

3. Performance Measurements

Many studies exist on performance measurement, as discussed by Smith (2016). Beginning with Jensen's (1968) single risk factor model using the market risk premium, the development in risk factor models is extended by Fama and French (1992) who present a three-factor model that adds a firm size premium and a style premium. Carhart (1997) adds a momentum factor with the idea of an incremental risk premium from high-momentum stocks versus low-momentum stocks. However, these performance measurements are more suitable for mutual funds than hedge funds because unlike mutual funds, hedge funds make use of a wider array of investment vehicles to pursue their objectives. Thus, a proper hedge fund performance measurement should reflect the wider range of risk factors.

For hedge fund performance measurement, Fung and Hsieh's (2004) seven-factor model is generally accepted as a standard. The first two components among the seven factors are major risk factors for a sizable portion of the industry, and represent equity ABS factors which includes (1) market risk and (2) the spread between small-cap stock returns and large-cap stock returns. The next two components are fixed income ABS factors. These factors include (3) the change in 10-

year Treasury yields and (4) the change in the yield spread between 10-year T-bonds and Moody's Baa bonds. The final three components are trend-following ABS factors which are based on Fung and Hsieh's (1997, 2001) observations that hedge funds follow trends in various markets. It includes (5) portfolios of lookback straddles on bonds, (6) portfolios on currencies, and (7) portfolios on commodities. In addition to seven-factor model, researchers enhance the model for emerging market hedge funds with an 8th factor that captures the return on emerging equity markets.

Bollen and Whaley (2009) also contribute in the literature on performance measurement in the hedge fund industry. In order to recognize dynamics in hedge funds, two econometric techniques that accommodate changes in risk exposures are studied: optimal change point regression and a stochastic beta model. The first model searches for a discrete number of dates on which factor loadings can shift. The second model specifies an autoregressive process for risk exposure. As a result of their comparison of the two models, the authors find that in the hedge fund context, the change point regression is generally more powerful than the stochastic beta model. With the result of superior techniques, the authors apply the change point regression model to the sample funds during the period of 1994 through 2005, and they find significant changes in the risk factor parameters in about 40% of sample hedge funds.

While there are abundant performance measurements, Ingersoll et al. (2007) argues that some performance measurements are vulnerable to manipulation strategies. Commonly used performance measurements such as the Sharpe ratio, Sortino ratio, information ratio, and Henriksson-Merton and Treynor-Mazuy timing measures are considered vulnerable in their paper, and they propose a manipulation-proof performance model (MPPM). The MPPM derived in the paper is shown in Equation 1.

$$\hat{\Theta} \equiv \frac{1}{(1-\rho)\Delta t} \ln \left(\frac{1}{T} \sum_{t=1}^T \left[\frac{1+r_t}{1+r_{ft}} \right]^{1-\rho} \right) \quad (1)$$

where $\hat{\Theta}$ statistics represents the estimated portfolio's risk-adjusted premium return, T is the total number of observations, and Δt is the length of time between observations, r_t is un-annualized rate or return at time t, and r_{ft} is the risk rate at time t. The coefficient ρ is the risk aversion coefficient, and according to them it should be selected to make holding the benchmark optimal for an uninformed manager. In short, as authors expression, $\hat{\Theta}$ represents the portfolio has the same score as does a risk free asset whose continuously-compounded return exceeds the interest rate by $\hat{\Theta}$. Ingersoll et al. points out the MPPM model resembles the "Risk-Adjusted Rating" which was developed for mutual funds by Morningstar in 2002. Although Ingersoll et al. (2007) provides an accurate way of measuring hedge fund performance, MPPM is not used in this analysis because the calculation of MPPM is out of the scope of this research.

Hypotheses

The main hypotheses for this study can be stated as follows.

Hedge fund performance hypothesis:

H₀: Net effect of hedge fund leverage on performance is not negative.

H₁: Net effect of hedge fund leverage on performance is negative.

Diseconomies of scale hypothesis:

H₀: Net effect of increase in fund size on performance is not negative.

H₁: Net effect of increase in fund size on performance is negative.

Data and Methodology

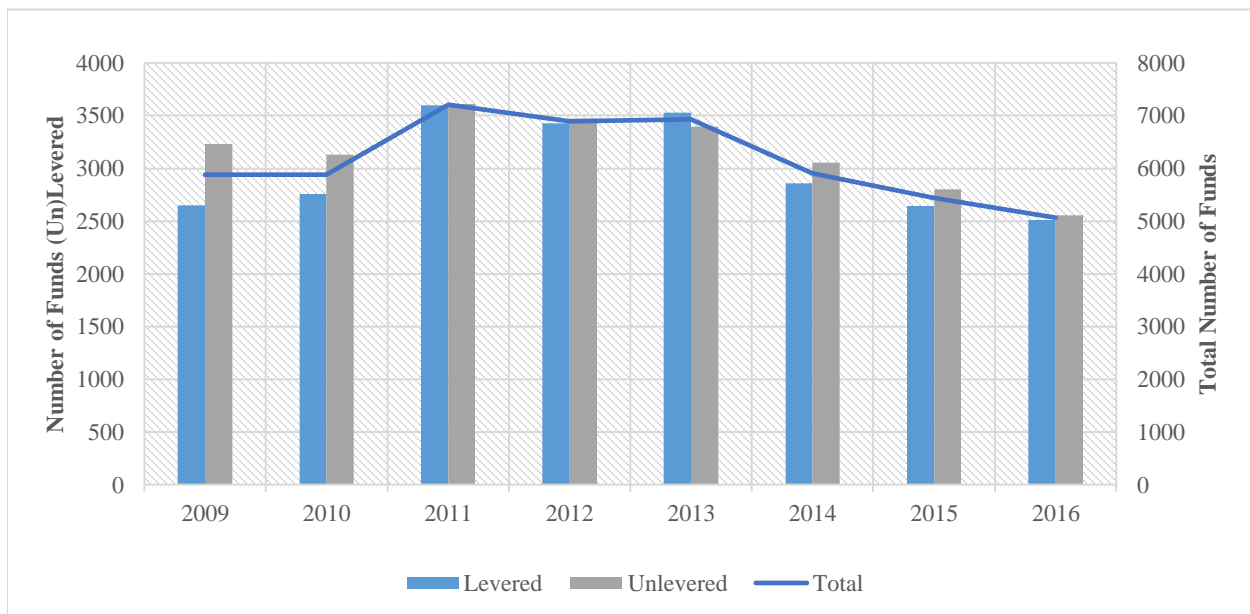
1. Data Description

The hedge fund data used in this paper are from the Lipper TASS database, which is one of the most important hedge fund data providers. The time period for the analysis is from 1994 to

2016. The TASS database is divided into two main categories: Live and Graveyard funds. The Live category contains hedge funds that are still active. Graveyard contains data that have been dropped out from the Live since 1994. Leverage in the TASS database is defined as the portfolio to margin ratio, yet in the case of managed futures funds, it is defined as margin to equity ratio. Based on the classification on hedge fund strategies in TASS database, hedge fund strategies are distinguished across 12 major categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, fund of funds, global macro, long/short equity hedge, managed futures, multi-strategy, and options strategy.

As of April 2016, TASS contains 20,108 individual hedge funds, of which 15,044 funds are from the graveyard and 5,064 funds are from the live database. Among the 15,044 of dissolved (graveyard) funds, 7,786 (51.75%) funds used leverage, and out of 5,064 of alive funds, 2,509 (49.55%) funds are using leverage. Chart 1 shows that since 2011, the number of funds in the Live

Chart 1
Number of Funds
 (based on Live fund data as of 2016)



Source: Lipper TASS database as of April, 2016, Live funds

category has been decreasing from 3,595 to 2,509, and it includes a higher proportion of unleveraged funds. In other words, the number of accumulated graveyard funds has been increasing since 2011 with the higher proportion of funds that used leverage. Considering the fact that AUM in the hedge fund industry has been increasing since the financial crisis period, existing hedge funds must have bigger volume in their AUM, yet fewer entities exist. Furthermore, the data shown suggests that usage of leverage might be one of factors that causes hedge funds to be dissolved.

Table 1 presents summary statistics of leverage use across various hedge fund strategies. The information is based on the TASS database as of April 2016, and it shows frequency of leverage use for each strategy. Among 12 strategies in both the graveyard and live databases, 9 strategies contain more than 50% of funds that use leverage. There are three common high leverage strategies in both dissolved and live funds: convertible arbitrage, fixed income arbitrage, and global macro. Convertible arbitrage is the category with highest leverage use with 73.86% for dissolved funds and 82.93% for live funds. Along with fixed income arbitrage, convertible arbitrage, by its nature uses high leverage in order to produce meaningful returns on its returns. Global macro also implies high leverage use in its strategy. Fund of funds is the category that uses least leverage; 36.07% for dissolved funds and 37.51% for live funds. There are two strategies that display high leverage use in dissolved funds but low leverage use in live funds. 46.15% of dedicated short bias in dissolved funds used leverage whereas only 16.67% are using leverage in live funds. Options strategy as well, used relatively high leverage (46.65%) in dissolved funds, yet only 9.09% are using leverage in live funds. However, since the Live category does not contain enough number of dedicated short bias and options strategy, it is hard to conclude that two strategies have inconsistent weight of leverage.

Table 1

Summary statistics of leverage use across various hedge fund strategies

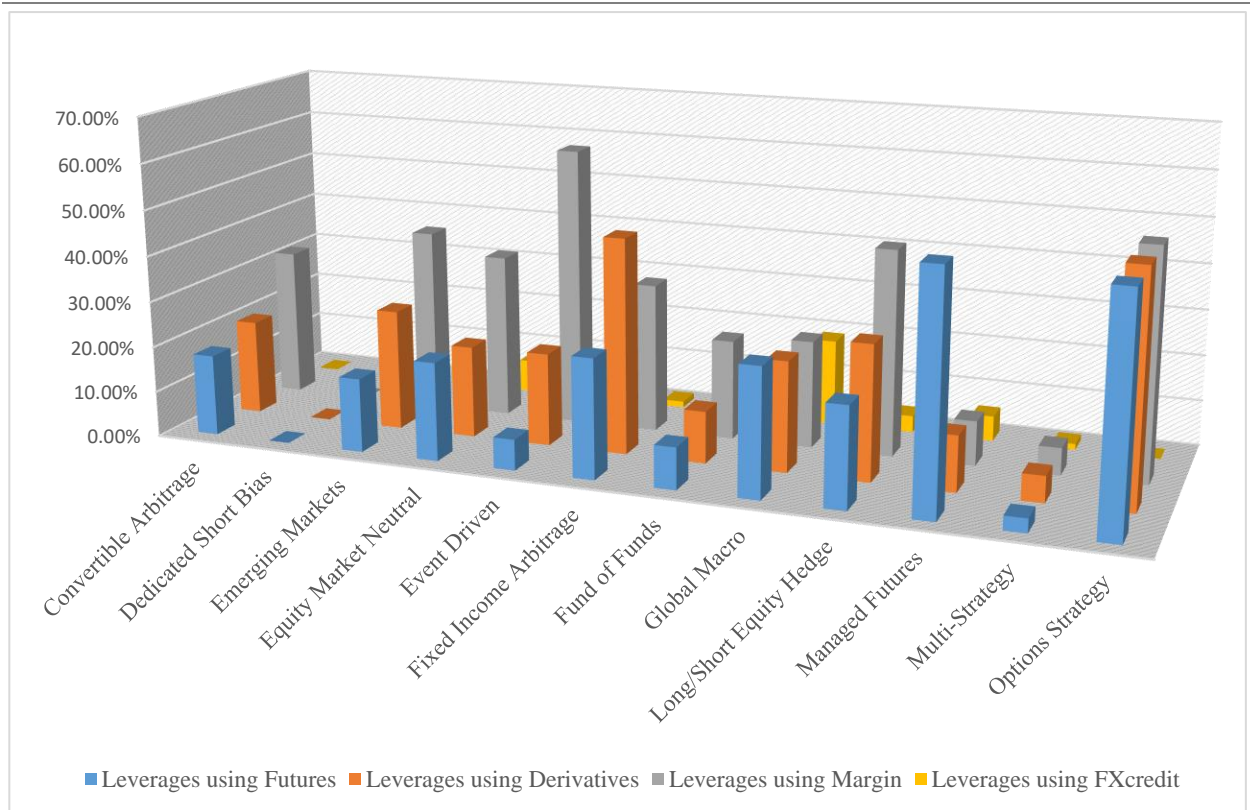
Graveyard 2016	Funds Leveraged	Funds Unleveraged
Convertible Arbitrage	195 (73.9%)	69 (26.1%)
Dedicated Short Bias	24 (46.2%)	28 (53.8%)
Emerging Markets	516 (60.7%)	334 (39.3%)
Equity Market Neutral	356 (57.9%)	259 (42.1%)
Event Driven	365 (52.3%)	333 (47.7%)
Fixed Income Arbitrage	262 (64.5%)	144 (35.5%)
Fund of Funds	1830 (36.1%)	3243 (63.9%)
Global Macro	584 (69.5%)	256 (30.5%)
Long/Short Equity Hedge	1922 (58.6%)	1356 (41.4%)
Managed Futures	638 (68.3%)	296 (31.7%)
Multi-Strategy	867 (54.4%)	727 (45.6%)
Options Strategy	21 (45.7%)	25 (54.3%)
SUM	7580 (51.7%)	7070 (48.3%)

Live 2016	Funds Leveraged	Funds Unleveraged
Convertible Arbitrage	34 (82.9%)	7 (17.1%)
Dedicated Short Bias	1 (16.7%)	5 (83.3%)
Emerging Markets	118 (50.0%)	118 (50.0%)
Equity Market Neutral	70 (56.0%)	55 (44.0%)
Event Driven	89 (52.0%)	79 (47.0%)
Fixed Income Arbitrage	77 (65.3%)	41 (34.7%)
Fund of Funds	634 (37.5%)	1056 (62.5%)
Global Macro	154 (60.4%)	101 (39.6%)
Long/Short Equity Hedge	494 (54.1%)	419 (45.9%)
Managed Futures	164 (53.4%)	143 (46.6%)
Multi-Strategy	555 (63.4%)	321 (36.6%)
Options Strategy	2 (9.1%)	20 (90.9%)
SUM	2392 (50.3%)	2365 (49.7%)

Table 1 presents the distribution of leverage across various fund strategy categories. Data used are from the Lipper TASS database as of April 2016. This table excludes strategy titled “other fund” and “undefined” funds in order to represent clear classification of fund strategy. Thus numbers displayed on the table differ from described numbers in page 8 of this paper.

The sources of leverage in the TASS database are classified into 4 categories: Via Futures, Via Derivatives (options and forwards), Via Margin, Via Foreign Exchange (FX) Credit. Hedge funds that trade futures, options, and forwards are leveraged by its nature. As stated in the Lipper TASS data description, margin in the database is not applicable to pure managed futures funds, and for a non-managed future funds it refers to funding positions through a brokerage house/counter party by using the securities in the fund's portfolio as collateral against which the fund borrows cash. FX Credit is assessed by houses/brokers and given credit limits to the fund up to which it can trade with them, and it is generally restricted to leveraged currency funds only. Table 2 presents sources of leverage across various hedge fund strategies. Variation in sources of leverage exist for each hedge fund strategy. Chart 2 displays the dispersion of sources of leverage in percentage terms that is calculated number of funds using each source of leverage divided by the number of leveraged fund for each strategy. Event Driven is the category with the highest proportion (60.67%) of margin as a source of leverage, and fixed income arbitrage uses highest use of derivatives (46.75%). The overall tendency of sources of leverage partially follows the transaction-cost saving hypothesis from previous study of Deli and Varma (2002), which suggests that choice of derivatives follows the funds' main underlying assets traded, and thus results in savings on transaction cost. This observation is also similar to the result of Chen (2011), where choice in source of leverage tends to follow funds' underlying assets traded. For example, managed futures showed the highest use of futures (51.22%) as a source of leverage.

Chart 2
Percent Sources of Leverage across Hedge Fund Strategy
 (Based on Live fund data as of 2016)



Note that the Live 2016 category does not contain enough number of dedicated short bias and options strategy, and thus graph displayed for two strategies are not valid for comparison.

Source: Lipper TASS database as of April, 2016, Live funds

Table 2

Summary statistics of sources of leverage across various hedge fund strategies

(Number of Funds)

Graveyard 2016	Futures	Derivatives	Margin	FXcredit
Convertible Arbitrage	8	27	106	2
Dedicated Short Bias	0	3	9	0
Emerging Markets	107	176	246	55
Equity Market Neutral	36	55	162	14
Event Driven	37	85	220	13
Fixed Income Arbitrage	82	96	145	34
Fund of Funds	340	467	489	338
Global Macro	219	185	165	129
Long/Short Equity Hedge	339	492	1099	64
Managed Futures	457	138	115	92
Multi-Strategy	120	136	186	29
Options Strategy	6	9	8	1

Live 2016	Futures	Derivatives	Margin	FXcredit
Convertible Arbitrage	6	7	11	0
Dedicated Short Bias	0	0	0	0
Emerging Markets	19	31	47	8
Equity Market Neutral	15	14	25	5
Event Driven	6	18	54	2
Fixed Income Arbitrage	20	36	25	1
Fund of Funds	58	72	138	28
Global Macro	43	37	36	29
Long/Short Equity Hedge	108	145	221	18
Managed Futures	84	20	16	9
Multi-Strategy	17	32	33	7
Options Strategy	1	1	1	0

Table 2 presents the distribution of sources of leverage across various fund strategy categories. Data used are from the Lipper TASS database as of April 2016. This table excludes “other fund” and “undefined” funds in order to represent clear classification of fund strategy.

2. Data Biases

Hedge funds are not obligated to report return data, and have minimal regulation. These characteristics cause hedge fund databases to have tendency of reporting biased results. The Lipper TASS database is no exception. Although regarded as important database, it is not free from biased results, and needs to be adjusted. There are several well known biases for hedge fund data. A self-selection bias occurs when fund managers incubate several funds, and only report the outperformers while they dissolve the underperformers. Instant history bias (also known as backfill bias) occurs when managers submit return data for initial months of a surviving hedge fund in order to take effect from past returns. Due to mean reversion and self-selection bias, subsequent returns are likely to be lower, and results in overall exaggeration on fund performance. When analyzing hedge fund, survivorship bias occurs if only surviving funds are considered. For this reason both live and graveyard database are considered in order to avoid survivorship bias that is reported by Liang (2000). Furthermore, frequently observed extreme dispersion of hedge fund returns is likely to distort the shape of return sample. Thus, to avoid misrepresentation from outliers, winsorizing is needed. Winsorizing is a transformation of extreme returns into an upper and lower percentile (e.g., the 1st and 99th percentiles), so that extreme outliers do not excessively influence the results.

3. Methodology

To address the question of whether individual hedge funds' use of leverage is stable over the years, TASS data between 2009 and 2016 are examined. Only those funds for which leverage is stable throughout this period are retained in the sample. TASS data on leverage usage was not

available prior to 2009, so this study assumes that average leverage was stable even prior to that time.

Following the method of Chen (2011), this study only includes funds with inception date after 1994 in order to mitigate survivorship bias reported by Brown, Goetzmann, Ibbotson, and Ross (1992) since TASS database does not report the returns of dissolved funds prior to 1994. Also in order to avoid backfilling bias and incubation bias, return data before the initial reporting date are excluded based on the ideas of Ackerman, McEnally, and Ravenscraft (1999) and Evans (2010). Among numerous graveyard fund data, only funds with “DropReasonID #1” (fund liquidated) are considered to exclude other reasons for drop out (e.g., fund no longer reporting, unable to contact fund, fund closed to new investment, etc.) and to induce meaningful use of dissolved funds.

The forementioned three performance measurements including Fung and Hsieh’s (2004) seven and eight-factor alpha, strategy-adjusted return, and style-adjusted return are used. Because the Fung and Hsieh alpha displayed high dispersion in its data, extreme returns are winsorized into a upper and lower 1 percentile of the entire distribution. Calculation of the strategy-adjusted return subtracts average of geometric return for each strategy from the given fund’s return data. Note that the return data from the TASS database are displayed net of management fees, which makes calculation simple. Style adjusted return follows the same process of calculation.

This study includes eight control variables that are likely to impact the usage of leverage. The control variables include: strategies, use of derivatives, initial AUM, high-watermark, use of futures, use of margin, use of foreign exchange credit, and offshore funds. Although the TASS database reports investment strategies for all funds, this study groups 11 strategies into four main

styles for the sake of brevity. The four styles of hedge fund investment include: the directional style (including dedicated short bias, emerging market, global macro, and long/short equity), the relative value style (including convertible arbitrage, fixed-income arbitrage, and equity market neutral), event driven style (including event driven and multi-strategy), and fund of funds style. This grouping is similar to that used by Agarwal, Daniel, and Naik (2009) and Chen (2011). The way of grouping reflects the market-wide risk since each style has different sensitivity to market fluctuations. The managed futures strategy is excluded from this paper in order to maintain a consistent definition of the “leverage” variable. Based on the TASS database description, leverage for managed-future strategy is expressed as margin to equity while leverage for other strategies are displayed as portfolio value to margin value (similar to an equity multiplier, the third term in DuPont analysis).

Because fund asset size and degree of leverage are considered key variables, this study carefully examines the related data in the TASS database. The size of each hedge fund is measured by initial AUM in order to avoid interaction between fund size and performance because after the initial month of hedge fund inception date, fund performance is likely to affect its AUM and vice versa. In light of previous literature regarding the size of AUM and the degree of leverage for hedge funds, it appears that the data in the TASS database for “average leverage” and “maximum leverage” may be reported on an inconsistent scale. The data have wide dispersion in both variables, and large portion of the data has unrealistic values. In order to mitigate the noise for size of a fund, funds with initial AUM lower than \$10 million are excluded following the idea of Yin (2016). The rationale for taking fund size as a key variable comes from abundance of preceding literature about the scale vs. performance relation.

In June 2009, the U.S. economy started to recover from the financial crisis, and entered an expansion phase. During that period, the hedge fund industry exhibited remarkable growth in its assets under management (AUM). According to Barclay Hedge, the hedge fund industry had \$2.948 trillion of AUM in the second quarter of 2016. With the high growth in the industry's AUM, this paper considers whether hedge fund leverage mitigates diseconomies of scale (Chen, Hong, Huang, and Kubik (2004)) that has been documented in all types of managed investment including mutual funds and hedge funds. Based on the correlation with the fund size, high-watermark is also a control variable in this study. Research of Yin (2016) suggest that performance fee, which is a unique feature of the hedge fund industry, does not mitigate the conflict between hedge fund managers and investors because the managers are able to gain more profit on their management fee with increased AUM rather than receiving performance fee which requires high fund performance. This study includes high-watermark as a dummy variable because the existence of a high-watermark is likely to drive hedge fund managers to care more about increasing fund's AUM, and thus is likely to result in lower performance.

While the initial AUM of the TASS database displayed noise, the degree of average leverage had truly unrealistic dispersion in its values, and no studies that control for the noise have been found. Thus, for better interpretation of displayed numbers, this study sets up transformation rules for the degree of leverage. Table 3 shows the transformation rule where X represents the maximum leverage that distinguishes normality for each strategies. The maximum point X is determined based on comparison of results from Ang et al. (2011) and Schneeweis et al. (2005) where the studies describe average leverage for each strategy. The dispersion for the degree of leverage within the TASS database is also considered. This study assumes that maximum leverage of normality for the directional style is gross leverage of 20, the relative value style is 41, and 10

for both event-driven and fund of funds. For brief examples, if a given number is a leverage of 75, instead of interpreting it as gross leverage of 75 where the sum of long and short position of the fund is 75 times of its margin, this study interprets 75 as a liability of the fund, and transforms it

Table 3
Transformation Rules for Degree of Leverage

Average Leverage	Assumption and Transformation
Leverage < 1	Ignore, as 8 only observations are in this range.
$1 \leq \text{Leverage} < X$	Interpret it as a correct gross leverage value.
$X \leq \text{Leverage} < 100$	Given number is interpreted as a liability. Transform to $(X+100)/100 = \text{Leverage}$
$100 \leq \text{Leverage}$	Given number is interpreted as an asset. Transform to $X/100 = \text{Leverage}$

into 1.75 $((75+100)/100)$. As a second example: if a given number is 300, this study interprets the number as an asset and transforms it into 3 $(300/100)$.

After the previous filtering processes for the data, 431 funds remain as a sample for a linear regression model. The model used in this study can be expressed as Equation 2.

$$\hat{y} = b_0 + b_1 \cdot X_1 + \sum_{i=1}^{12} b_{i+1} \cdot d_i + \sum_{i=13}^{23} b_{i+1} \cdot d_{i-11} \cdot X_1 \quad (2)$$

where \hat{y} denotes the three performance measures, X_1 is the degree of average leverage, d_i refers to 12 dummy variables to show the impact of control variables, and the multiplication of X_1 and d_i refers to full interaction which displayed as 11 dummy variables. The number of full interaction terms is different from the number of dummy variables because the interaction between use of leverage and high-watermark (one of the 8 control variables used in this research) is not likely to occur.

Empirical Analysis

This section tests the relation between degree of hedge fund leverage and risk adjusted performance. Among the three performance measures (including Fung and Hsieh seven and eight-factor alpha, strategy adjusted return, and style adjusted return) regressed on the degree of leverage, only strategy adjusted return shows statistically significant result. There was a strong evidence of heteroscedasticity in the initial regression after processing the Breusch-Pagan test. In order to mitigate the problem, robust standard errors are calculated. Table 4 shows the result of a robust regression for strategy-adjusted return as a dependent variable. Based on the result, a negative relationship between use of leverage and hedge fund performance is detected. The coefficient for the degree of leverage in this regression is -0.00185 with a p -value of 0.066 . The coefficient is not trivial since strategy-adjusted return is regressed in nominal scale instead of in percentage terms. The proper interpretation of the coefficient of -0.00185 in this study is that for every 1 increase in gross leverage, there is a 0.185% decrease in risk-adjusted performance. Another interesting observation from the robust regression result is evidence of diseconomies of scale in the leveraged funds. Leveraged funds with medium-sized AUM tend to show better performance than leveraged funds with large-sized AUM. In specific, with the p -value of 0.067 , medium-sized funds tend to show 0.1117% higher return than large-sized funds.

This study includes the post-financial crisis period where interest rate (LIBOR) is very low, which represents favorable conditions for hedge funds to use leverage. The cost of leverage can be represented as LIBOR since prime brokers charge a spread over LIBOR to a borrower. Even though this study includes the time period associated with a low cost of leverage, the relationship between hedge fund leverage and performance shows a negative coefficient. The negative relation is not likely to change in future circumstances unless the interest rate drops even lower than the

Table 4

Robust Regression result for strategy-adjusted return

Number of obs = 431
 F(24, 406) = 2.73
 Prob > F = 0.0000
 R-squared = 0.0770
 Root MSE = .00908

StrategyAdjustedReturn	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
RelativeValueStyle	.0002298	.0017829	0.13	0.897	-.003275	.0037346
DirectionalStyle	.0001259	.0015676	0.08	0.936	-.0029558	.0032076
EventDriven	.0029333	.0043996	0.67	0.505	-.0057155	.011582
RelativeXLev	.0007232	.0005427	1.33	0.183	-.0003437	.0017902
DirectionalXLev	.0006749	.0004354	1.55	0.122	-.0001809	.0015308
EventDrivenXLev	-.0016695	.0026314	-0.63	0.526	-.0068423	.0035032
HighWaterMark	-.001348	.0011579	-1.16	0.245	-.0036244	.0009283
CASEBLeverageZ3_2MD20R41E	-.0018655	.0010121	-1.84	0.066	-.0038552	.0001242
Futures	.0003214	.0012367	0.26	0.795	-.0021097	.0027525
Derivatives	.0012404	.0012209	1.02	0.310	-.0011597	.0036405
Margin	.0002238	.0014882	0.15	0.881	-.0027016	.0031493
FXCredit	-.0003921	.0016199	-0.24	0.809	-.0035765	.0027923
FutureXLev	.0001044	.0003389	0.31	0.758	-.0005618	.0007706
DerivativeXLev	-.0003732	.0002803	-1.33	0.184	-.0009243	.0001779
MarginXLev	.000408	.0005209	0.78	0.434	-.000616	.001432
FXCreditXLev	-.0005857	.0003504	-1.67	0.095	-.0012745	.0001032
Offshore	-.0038709	.0012772	-3.03	0.003	-.0063816	-.0013602
OffshoreXLev	.0001743	.0002726	0.64	0.523	-.0003617	.0007102
Small	.0002476	.0020793	0.12	0.905	-.00384	.0043353
Mid1	-.0001243	.0016421	-0.08	0.940	-.0033524	.0031037
Mid2	-.0005431	.0018039	-0.30	0.764	-.0040892	.003003
SmallXLev	.0007032	.0006932	1.01	0.311	-.0006595	.0020659
Mid1XLev	.001117	.0006077	1.84	0.067	-.0000776	.0023116
Mid2XLev	.0008588	.0006223	1.38	0.168	-.0003646	.0020822
_cons	.0044117	.0024851	1.78	0.077	-.0004737	.009297

Table 3 presents the result of robust regression for strategy-adjusted return. Highlighted rows represent degree of leverage and the interaction of leverage and size of the fund. The result shows that coefficient for each variable is -0.0018655 and 0.001117 with p -value of 0.066 and 0.067 respectively.

current era. Although interest rates are hard to forecast, recent data imply that interest rates are in an increasing trend, and the cost of leverage is not likely to decline.

Conclusion

This paper presents the net impact of hedge fund leverage on performance. The Lipper TASS database from 1994 to 2016 is used, where approximately 50% of the hedge funds use leverage. This paper continues the spirit of previous literature including Schneeweis et al. (2005)

and Ang et al. (2011). However, it is different from the previous literature by including the post-financial crisis era, and the time period offers an unusually low cost of leverage to hedge fund managers. Furthermore, this study includes 11 strategies of funds and 3 performance measurements including Fung and Hsieh seven and eight-factor alpha, strategy-adjusted return, and style-adjusted return. Among the three performance measures, only the regression for strategy-adjusted return as a dependent variable displays significant results. There are no statistically significant results observed in regressions on other performance measurements.

The result of robust regression shows a negative relation between hedge fund leverage and its strategy-adjusted return. For every 1 increase in gross leverage, 0.185% decrease in strategy-adjusted return is expected with the p -value of 0.066. Diseconomies of scale for leveraged funds is also observed in the analysis. With the p -value of 0.067, leveraged funds with medium-sized AUM tend to show 0.1117% higher performance than that of funds with large-sized AUM.

The outcomes of this study suggest two important implications. First, for most cases, hedge fund leverage is unlikely to give a positive impact on risk-adjusted performance because even in this time period when the conditions for leverage are very favorable, a negative relation between the two variables is observed. Furthermore, interest rates are not likely to decrease more than in the current period. Second, because leverage is one of the break points that distinguishes hedge funds and other managed investments, the negative impact of leverage on risk-adjusted performance suggests a warning to investors who have high return expectation for the hedge fund industry. It follows the idea of Lack (2012) where he criticizes the under-performance of the hedge fund industry, a phenomenon that he describes as the “Hedge Fund Mirage.”

The hedge fund data used in this paper are from the Lipper TASS database. However, AUM of the fund and degree of leverage in the database had unrealistic dispersion of values. In order to have accurate data, other data vendors such as Hedge Fund Research (HFR) or a large pool of fund of funds would be a good choice for future research. Furthermore, this paper does not include the managed futures strategy in order to maintain a consistent definition for leverage. Based on the TASS database description, leverage for the managed-futures strategy is expressed as margin to equity while leverage for other strategies are displayed as portfolio value to margin value. However, it will be better to include futures in the sample since 6.4% of all hedge funds use the managed-futures strategy, and 24.05% of all hedge funds use futures as a source of leverage.

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