The Big Squeeze: Capacity constraints and merger arbitrage hedge fund performance in the last two decades

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Abstract

The study proposes a model that explains the evolution of merger arbitrage strategy alpha since early 1990s. The paper demonstrates that the decline in alpha over time is related to the expansion of merger arbitrage capital relative to available arbitrage opportunities, and that the merger arbitrage spread acts as an important conduit though which this expansion has impacted alpha. The results indicate the existence of significant capacity constraints in the merger arbitrage hedge fund strategy and suggest that skill differences among US-focused merger arbitrage fund managers are unlikely to be reflected in differences in hedge fund returns realized by investors.

Keywords: hedge funds; merger arbitrage; capacity constraints.

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1 Introduction

Merger arbitrage or risk arbitrage is an investment strategy where the objective is to realize the spread between the acquisition price and the price at which the stock of a target trades subsequent to the announcement of an acquisition. Merger arbitrage is a popular investment strategy. Between 1990 and 2010 assets under management of U.S.-focused, U.S. dollar denominated merger arbitrage funds has grown from under $0.5 billion in early 1990s to over $2 billion in 2010 (see e.g., Hedge Fund Research Inc. or HFR, Lipper Tass). In this paper we examine the evolution of alpha of merger arbitrage funds since early 1990s. In particular, we show that a part of the variation in the alpha of merger arbitrage funds can be explained by changes in both the demand and supply of capital devoted to merger arbitrage. In addition, we document several interesting facts such as, the decline of returns of M&A hedge funds and the lack of persistence in performance of M&A funds.

Our paper is related to studies on merger arbitrage as well as studies that examine evolution of hedge fund alphas. For example, Larcker and Lys (1987), Mitchell and Pulvino (2001), Baker and Savaşoğlu (2002), and Jindra and Walkling (2004) report economically and statistically significant excess returns related to merger arbitrage.

A number of studies have analyzed the evolution of alphas over time and the extent to which capital inflows have contributed to the decline in alphas. Fung, Hsieh, Naik, and Ramadorai (2008) analyze fund-of-funds and find structural breaks in hedge fund risk exposures, where structural breaks represent statistically and economically significant changes in systematic risk. Fung, Hsieh, Naik and Ramodarai also find that after taking into account the change in systematic risk, alphas tend to decline following capital inflows. Similarly, Naik, Ramadorai, and Stromqvist (2007) find capital inflows to precede declines in alphas of four out of eight hedge fund strategies. Naik, Ramodarai and Stromquist also take into account the structural break points used by Fung, Hsieh, Naik and Ramodarai. Jetley and Ji (2010) focus on merger arbitrage funds and report a decline in both returns and alphas of merger arbitrage funds since the early 2000s. Jetley and Ji indirectly link the decline in alphas and returns to capital inflows.
by using volume of trading in a targets’ stock around the announcement date as a proxy for capital flows. A number of other studies, such as Zhong (2008) and Jagannathan, Malakhov, and Novikov (2010) have also analyzed the decline in alphas over time.

We extend this literature in several ways. First, we demonstrate a negative relationship between M&A hedge fund alphas and capital devoted to the merger arbitrage strategy. The characteristics of the merger arbitrage strategy are such that it enables one to develop reasonable proxies for both demand and supply of merger arbitrage capital. In addition, the merger arbitrage spread – the amount by which the bid price exceeds the post-announcement price of a target – allows one to precisely measure the unlevered profit potential of the strategy. Our contribution to the literature builds on the inherent measurement-related advantage of merger arbitrage with respect to both the strategy’s capacity (supply and demand of capital) and profitability. We exploit the fact that the size of the merger arbitrage market is limited by the volume of M&A deals at any point in time. In other words, for a given period of time, the dollar value of deals announced during that period is a good proxy for the demand of merger arbitrage capital. Further, assets under management of merger arbitrage funds may be used as a proxy for the supply of merger arbitrage capital. Thus by being able to separately track the demand and supply of merger arbitrage capital we develop a measure a merger arbitrage capital abundance (MACA), which we use to explain the evolution of alphas of merger arbitrage funds.

Consistent with Jetley and Ji (2010) and Fung, Hsieh, Naik, and Ramadorai (2008), we find that large hedge fund returns and alpha related to merger arbitrage prevailing in the 1990s have declined substantially. We directly link the decline of alphas to an increase in MACA – our measure of merger arbitrage capital abundance – and to the decline in merger arbitrage spread. We establish this link by first using the seven-factor model developed by Fung and Hsieh (2004) to obtain an out-of-sample forecast of merger arbitrage strategy alpha over time. We then explore the relationship between forecasted alpha and two variables: one that proxies for the amount of capital available for merger arbitrage relative to existing arbitrage opportunities and another that proxies for merger arbitrage profitability. We find negative
relationship between merger arbitrage capital abundance variable and alpha, as well as a positive relationship between arbitrage spread and alpha. The relationships also survive various robustness checks designed to address possible biases related to hedge fund data collection, return properties and model specification. Lastly, we find that these two variables accurately predict the evolution of average merger arbitrage strategy alpha over time.

We also document lack of long term persistence in the performance of M&A hedge funds, both in absolute and relative terms. Absolute persistence refers to the ability to generate similar returns over time. So if a hedge fund was able to generate a 6 percent return in say 1998, absolute persistence would imply returns of about 6 percent in years subsequent to 1998. The decline in average absolute performance is consistent with the observed increase in capital devoted to risk arbitrage as well as the decline in arbitrage spread.

The lack of persistence in relative returns – the inability of merger arbitrage funds to consistently report returns that would put them in the top quartile – has interesting implications. A lack of relative persistence suggests that either skills do not vary much across merger arbitrage funds or difference in skill are less relevant than strategy-wide factors. The lack of persistence in relative returns coincides with narrowing of the distribution of arbitrage spreads over the last two decades (see e.g., Jetley and Ji (2010)). Because arbitrage spread is the primary source of profit for merger arbitrage hedge funds, narrowing arbitrage spread distribution implies that particularly skilled fund managers, if they exist, would find it more difficult to differentiate themselves from mediocre managers. These results build on the previous studies of persistence in hedge funds’ performance. Brown, Goetzmann, and Ibbotson (1999) using 1989-1995 data found no persistence in hedge fund returns for 1 year horizons, Agarwal and Naik (2000) found evidence of persistence for quarterly horizons, suggesting that persistence in returns exists over short time horizons. Fung, Hsieh, Naik, and Ramadorai (2008) found that between 1994 and 2005 only 22% of all hedge funds delivered positive and statistically significant alpha. A more recent paper by Jagannathan, Malakhov, and Novikov (2010) indicates persistence over 3 year horizon for top hedge fund managers and no persistence for the rest.

As far as we know, our paper is the first to take into account both the demand and supply
of merger arbitrage capital to explain the evolution of alphas of merger arbitrage funds. Our findings also show that cross-sectional variation in returns has declined sharply in recent years, indicating that merger arbitrage hedge fund managers have found it difficult to distinguish themselves from each other. This conclusion is further corroborated by the lack of long term persistence in performance of merger arbitrage hedge funds. Taken together these results suggest that managerial ability (or skill) to deliver returns did not vary much across merger arbitrage hedge funds in the recent years due to increased capital availability, competition among funds and an overall decline in profitability.

The rest of the paper is structured as follows. The next section describes stylized facts regarding the performance of merger arbitrage hedge funds over the last two decades, and develops our testable hypotheses. Section 3 describes the empirical strategy. Section 4 discusses the results. Section 5 concludes.

2 Stylized facts and hypotheses development

The last two decades saw a significant increase in popularity of hedge funds. The amount of assets under management has grown by fourteen fold from $118 billion in 1997 to $1.7 trillion in 2010. Assets under management of U.S. focused merger arbitrage hedge funds grew fourfold to over $2.0 billion in 2010. Figure 1 plots the natural logarithm of the ratio\(^1\) of assets under management of U.S. focused, U.S. dollar denominated merger arbitrage funds to value of announced M&A deals over time.\(^2\) Additionally, we estimate time trend of this measure using locally weighted scatter plot smoothing (loess). The figure indicates a strong upward trend in merger arbitrage capital relative to the value of deals announced from 1994 through

\(^1\)For each calendar month the numerator is the sum of assets under management of U.S.-focused hedge funds whose assets are denominated in U.S. dollars as reported by HFR and Lipper Tass databases. The denominator is the sum of values of M&A bids announced in a given calendar month net of assumed liabilities as reported by Thomson ONE Banker database. We used only bids that, if completed, will result in change in control defined as increase in ownership by the bidder from less than 50% to more than 50%.

\(^2\)This ratio is likely to understate capital abundance as we do not take into account assets under management for funds that are not specifically U.S.-focused. Such funds may also allocate a part of their portfolios to U.S. mergers and acquisitions. We identified U.S. focused funds by using regional investment focus variable in HFR and Lipper Tass databases. We used fund asset currency denomination variable to identify U.S. dollar denominated funds.
early 2000s. Subsequently, the ratio declines somewhat, and then seems to level off starting in 2006.

[Insert Figure 1 here]

The increase in merger arbitrage capital through early 2000s has been accompanied by a downward trend in merger arbitrage spread over the same period. Figure 2 depicts the evolution of median quarterly arbitrage spread for friendly cash only bids. Consistent with Jetley and Ji (2010) we observe a decline in the spread between 1994 and early 2000s, reaching the bottom around 2002 and 2003. After 2003 the median arbitrage spread increases slightly, spiking in the last quarter of 2008 and the first quarter of 2009 and then sharply declining in the latter part of 2009 and in 2010. Despite these fluctuations the merger arbitrage spreads exhibits a broad decline between 1990s and 2000s. The same conclusions hold when we use locally weighted scatterplot smoothing to trace the median arbitrage spread trend over time.

[Insert Figure 2 here]

Corresponding to the increase in merger arbitrage capital and to the broad decline in merger arbitrage spread over time is the decline in merger arbitrage hedge fund returns. Given trends reported in Figures 1 and 2 we compare hedge fund performance between 1994 to 2002 period and 2003 to 2010 period. The average monthly return for HFR merger arbitrage hedge fund index fell from 88 basis points in the 1994 – 2002 period to 50 basis points in the 2003 – 2010 period. The decline in average returns can also be seen for individual merger arbitrage hedge funds. In our sample of hedge funds formed prior to 2003, the median return declines from 82 basis points per month in 1994-2002 period to 41 basis points per month in 2003 – 2010 period. Figure 3 shows the box plot of the distribution of the M&A hedge funds’ returns indicating

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3 As in Figure 1 we used only bids that, if completed, will result in change in control defined as increase in ownership by the bidder from less than 50% to more than 50%. To calculate the arbitrage spread we subtract target’s stock price one trading day after offer bid announcement from the offer’s bid price and divide the difference by target’s stock price one trading day after offer bid announcement. For multiple bid auctions we use the first offer’s bid price and stock price one trading day after the day of the first bid announcement. Multiple bidders are defined as in Bates, Becher, and Lemmon (2008) and Bates and Lemmon (2003). We remove outliers by excluding the top and the bottom 1% of merger arbitrage spread values and use remaining sample of offer bids to calculate quarterly median arbitrage spread.

4 Some of those funds are not in HFR M&A hedge fund index.
significant decline in the median, 25th and 75th percentiles of the return distribution over time.

Thus, Figures 1 through 3 suggest that increase in merger arbitrage capital prior to 2003 not only reduced the returns but also muted the differences between competing M&A arbitrage hedge funds. A closer examination of the individual hedge funds’ returns points to the compression of hedge fund returns over time. Figure 3 indicates that while during the 1994 – 2002 period the interquartile range for average monthly merger arbitrage hedge fund returns was 47 basis points, in the 2003 – 2010 period, the interquartile range has shrunk by more than 50 percent to 19 basis points per month. This result is consistent with the Jetley and Ji (2010) who report a compression of merger arbitrage spreads during roughly the same period.5

[Insert Figure 3 here]

Another interesting aspect of hedge fund performance is its persistence. Is good (bad) performance in one period followed by good (bad) performance in the subsequent period? Ability to identify funds with persistent performance helps investors to identify funds that are consistently good and avoid funds that are consistently bad. Early research found no or little persistence over short time horizons (quarterly or annual), while more recent literature found differences across funds and some intermediate term (3 year horizon) persistence among alpha producing funds (see e.g. Brown, Goetzmann, and Ibbotson (1999); Agarwal and Naik (2000); Fung, Isiheh, Naik, and Ramadorai (2008); Zhong (2008); Jagannathan, Malakhov, and Novikov (2010)). Our results also suggest lack of persistence in the merger arbitrage hedge funds’ performance. Figure 4 plots average merger arbitrage hedge fund returns in the 1994 – 2002 period against average merger arbitrage hedge fund returns in 2003 – 2010 period. The average returns for individual funds exhibit substantial variation in the earlier period which declines noticeably in the later period. This can be gauged by comparing the distribution of returns along the horizontal axis to those along the vertical axis. As shown in Figure 4, the reduction is not limited only to best performing funds. Generally, funds in the upper part of return distribution in the 1990s have seen their performance decline substantially.6 Conversely,

5See Table 2, page 57 of Jetley and Ji (2010).
6They are located below the 45 degree line on Figure 4.
funds that underperformed in the 1994 – 2002 period improved their performance in the later period.\footnote{We find similar result when we compare individual hedge funds' Sharpe's ratios.}

[Insert Figure 4 here]

The decline in returns as well as the reduction in variation of returns shown in Figures 3 and 4 is consistent with Zhong (2008) and Fung, Hsieh, Naik, and Ramadorai (2008). Zhong found that the decrease in hedge funds' alpha is driven primarily by decline in alphas among top performing funds. Fung, Hsieh, Naik and Ramadorai found that capital inflows in alpha-producing funds have decreased the ability of such funds to continue delivering alpha.

Because hedge funds report returns and assets under management on voluntary basis hedge fund databases are subject to a number of well-known biases. Our primary concern is with survivorship, backfill and serial correlation biases (e.g., Jagannathan, Malakhov, and Novikov (2010)). The backfill bias arises when a fund joins a hedge fund database such as HFR or Tass databases bringing with it its return history. If a hedge fund chooses to join a database during the period of relatively high performance using backfill observation may create an appearance of declining performance over time. The survivorship bias exists when performance measurements do not take into account performance of funds that have been liquidated or stopped reporting. If the decision to liquidate or stop reporting is systematically related to performance, the results will be biased upward when performance of such funds is not taken into account. Investments by hedge funds in relatively illiquid securities are known to be one of the sources of the serial correlation bias.

It is unlikely that the results shown in Figures 3 and 4 are due to the survivorship or backfill biases. To begin with, Liang (2000) finds that the performance of merger arbitrage funds in HFR and Tass databases exhibit little or no survivorship bias. However to investigate survivorship bias we analyze the performance of both living funds and funds that either liquidated or stopped reporting as of the end of the sample period (2010). Out of 30 hedge funds in our HFR/Tass sample with date of inception prior to 2003, 14 funds continued to be
active through the end of the sample period, another 14 funds liquidated and 2 funds stopped reporting after 2002. Notably 11 out of 14 funds that liquidated did so between March and November 2008, while 2 funds that stopped reporting did so in June 2008. Thus, over 50 percent of funds in our sample that existed prior to 2003 liquidated or stopped reporting in 2008. Because the two funds that have stopped reporting did so in 2008, it is unlikely that their decision is driven by superior performance. Consequently, it is highly improbable that our results are driven by the survivorship bias.

Additionally, to check if the results reported in Figures 3 and 4 are sensitive to the inclusion of observations close to financial crisis of 2008, we exclude funds’ performance subsequent to December 2006. The results remained the same – we still find the decline in and compression of merger arbitrage hedge fund returns as well as lack of persistence for active and liquidated funds. The presence of data from the recent financial crisis does not appear to influence our conclusions.

To check if the results are influenced by backfill bias we exclude all observations prior to date of inclusion in HFR or Tass databases. Again, our results continue to hold.

Getmansky, Lo, and Makarov (2004) argue that the trading in illiquid securities by hedge funds may lead to serial correlation in hedge fund returns that would make hedge fund returns appear to be less volatile and hence bias results in favor of finding performance persistence. In general, one would not expect merger arbitrage hedge fund returns to be significantly impacted by serial correlation bias. This is because merger arbitrage funds invest in relatively liquid securities – common equity of target firms. Our sample of hedge funds confirms this intuition. We find that the average first order autocorrelation in hedge funds’ returns is 0.16, and that the autocorrelation estimates are statistically insignificant for 75% of hedge funds in our sample. Because the existence of serial correlation in hedge fund returns would work against finding results reported in Figures 3 and 4, we conclude that serial correlation is not strong enough to affect conclusions reported in those figures. Nevertheless, to account for the impact of

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8 We use the last date of reported assets as an indicator of when the fund liquidated or stopped reporting.
9 Results available upon request.
autocorrelation in hedge fund returns we use serial correlation robust Newey and West (1987) standard errors in our hedge fund performance models. We find that our results are not sensitive to assumptions regarding autocorrelation of hedge funds returns.

We have also looked at persistence of relative performance. Again there appears to be no relationship between funds’ relative performance rankings in 1994 – 2002 and in 2003 – 2010 periods - the Spearman’s rho\textsuperscript{10} for the average monthly merger arbitrage hedge fund returns is only –0.03 and the p-value is 0.89. Thus, a performance leader or laggard in an earlier period is no more or less likely to remain in the same position relative to other funds in the latter period. This inability to deliver to investors consistently superior (or inferior) returns relative to peers is indicative of limited or no role of skill in merger arbitrage strategy during the period. This result is also illustrated in Table 1. The table compares hedge fund rankings using average return quartiles in 1994 – 2002 and 2003 – 2010 periods. In each period we rank each fund of by average raw monthly return within that period, and in each period we sort each fund into a return quartile. The table examines whether a fund was able to remain in the same quartile during the two time periods – 1994 – 2002 and 2003 – 2010. The table shows whether the relative performance improved or declined across the two periods. If there was persistence in relative performance one should observe all hedge funds clustering on the main diagonal. Instead, we see that performance rank in 1994 – 2002 period is typically followed by either increase or decline in rank in the 2003 – 2010 period. This result survives if we exclude backfilled observations from our sample.

[Insert Table 1 here]

The stylized facts point to the possibility that the decline in merger arbitrage hedge fund returns over the last two decades has been driven by the increasing merger arbitrage capital and the decline in the level and variability of merger arbitrage spreads. The findings presented above are consistent with Jetley and Ji (2010) who document a 400 basis points decline in merger arbitrage spread between early 1990s and mid-2000s.

\textsuperscript{10}Using 30 merger arbitrage hedge funds with date of inception prior to 2003. Defined as correlation between the rankings of values of two variables.
We conjecture that strategy-wide factors such as the abundance of merger arbitrage capital and the evolution of the merger arbitrage spreads have played an important role in the decline of merger arbitrage fund returns and strategy alpha in the last two decades. Specifically, we test the following hypotheses in order to investigate our conjecture:

**Hypothesis 1** An increase (decrease) in supply of merger arbitrage capital relative to demand for the same has negative (positive) impact on the performance of merger arbitrage hedge funds.

**Hypothesis 2** An increase (decrease) in merger arbitrage spread has positive (negative) impact on the performance of merger arbitrage hedge funds.

3 Empirical Strategy

3.1 Data and sample construction

Our empirical strategy focuses on determinants of alpha. To calculate alpha we first obtain excess returns. We use two measures of strategy level excess returns to ensure that our results are not driven by a particular measure. We use a monthly return on HFR's Merger Arbitrage Strategy Index (HFRIMAI)\(^{11}\) in excess of monthly return on 1-month T-bill. Since HFRIMAI is an equally weighted index of merger arbitrage hedge funds we also use asset-weighted return of individual funds in our HFR/Tass sample to develop another measure of sector excess returns. In particular, we identify all hedge funds in the HFR and Tass databases that are U.S.-focused merger arbitrage hedge funds with assets that are denominated in U.S. dollars. We also limit our sample to funds that reported returns and assets continuously since inception and that have formed prior to 2003.\(^ {12}\) These criteria leave 30 merger arbitrage hedge funds in our sample.

\(^{11}\)To be included in the index the merger arbitrage hedge fund must be listed in HFR database, and report monthly net of all fees performance and assets in U.S. dollars. Additionally to be included in the index the fund must have at least 12 month track record or at least $50 million in assets. See HFRI Hedge Fund Indices: Defined Formulaic Methodology, 2011.

\(^{12}\)The limitation on funds’ age enables us to test the impact of strategy wide factors on funds that formed during the period of relatively scarce arbitrage capital and high profitability (arbitrage spread). Hence, tracing performance of such funds over time should enable us to distinguish the long term effects of skill from the effects of strategy-wide factors on alpha.
3.2 Forecasting alpha

In order to investigate the impact of changes in merger arbitrage capital as well as changes in arbitrage spread on the performance of merger arbitrage hedge funds we begin by estimating the seven-factor return model developed by Fung and Hsieh (2004),

\[ r_t = \alpha + \beta_1(excess \ S&P500 \ return_t) + \beta_2(SC_t - LC_t) + \beta_3(\Delta T10Y_t) + \beta_4(\Delta(Baa - T10Y)t) + \beta_5PTFSBD_t + \beta_6PTFSFX_t + \beta_7PTFSCOM_t + e_t \]  

The dependent variable \( r_t \) is either a monthly return on HFR’s Merger Arbitrage Strategy Index in excess of monthly return on 1-month T-bill or an asset-weighted excess monthly return for 30 merger arbitrage hedge funds in our sample.

In order to calculate an asset-weighted excess monthly return we follow methodology of Naik, Ramadorai, and Stromqvist (2007). For each of the 30 merger arbitrage hedge funds in the sample we subtract current monthly 1-month T-bill return \( r_{ft} \) from current monthly raw fund return \( r_{it} \) and multiply the difference by current month’s asset weight. We add the resulting products together to obtain the asset weighted M&A arbitrage strategy excess return for a given month,

\[ \omega_{it}(r_{it} - r_{ft}) \]

In each month the asset weight for each fund is defined as \( \omega_{it} = \frac{AUM_{it}}{\sum_{i=1}^{30} AUM_{it-1}} \) where AUM are assets under management for fund \( i \).

Broadly speaking the seven factors or independent variables can be grouped into three categories.\(^{13}\) The first category includes factors that capture the exposure of returns to equity risk this would include – excess S&P500 return, which is the difference between the return on

\(^{13}\) See Fung and Hsieh (2004) for seven factor model development.
the S&P500 index and the 1 month T-bill, and $SC_t - LC_t$ which is the difference between the return on the S&P 600 Small Cap Index and the S&P500 Index for the month $t$. The second category captures exposure to interest rate and credit risk. In particular $\Delta T10Y_t$ is the change in the 10 year constant maturity treasury ("CMT") rate in month $t$, while $\Delta(Baa - T10Y)_t$ is the change in the difference between the yield of 10-year Baa rated securities and the 10-year CMT during month $t$. The last category captures exposures to trends in currencies, commodities and bond futures. These variables seem more suited for trend following hedge funds, however we have included them in our model to gauge robustness of results. The three factors are the return on portfolio of lookback straddles on bond futures (PTFSBD), return on a portfolio of lookback straddles on currency futures (PTFSFX), and return on a portfolio of lookback straddles on commodity futures (PTFSCOM).\footnote{A lookback straddle consists of two (floating strike) lookback options – a call and a put. A lookback call option gives its holder a right to buy the underlying asset at a minimum price prevailing over life of the option. A lookback put option gives its holder a right to sell the underlying asset at the maximum price prevailing over life of the option.} We estimate Equation (1) using ordinary least squares. To account for heteroskedasticity and/or serial correlation we calculate Newey and West (1987) 6-lag standard errors.\footnote{We find 1-lag autocorrelation to be around 0.20 for both dependent variables, declining to nearly zero with 6 lags.}

To forecast alpha for month $t$ we subtract the product of realized values of seven risk factors in month $t$ and seven estimated factor loadings from realized excess return $r_t$ in month $t$. We estimate factor loadings from the seven factor model over a 24 month period ending one month prior to month $t$. Thus to calculate January 1996 alpha we subtract the product of realized values of seven factors in January 1996 and the coefficients of the seven factor model estimated using monthly returns for the 24 month period ending December 1995 from realized excess return in January 1996. Thus, the alpha for a given month is an out-of-sample estimate of hedge fund returns in excess of the returns predicted by the seven common risk factors. Next, we shift our estimation and prediction window forward by one month and similarly calculate February 1996 alpha. We repeat this procedure until we reach the end of sample period. Because we use 24-month rolling window and our data starts in January 1994 the forecasted alpha is obtained from January 1996 onward.
3.3 Explaining alpha

To explain alpha we use two variables: A variable that captures the amount of available arbitrage capital relative to available merger arbitrage opportunities and a variable that captures unleveraged profitability of merger arbitrage strategy. We define the model as,

\[ \hat{\alpha}_t = \gamma_0 + \gamma_1 MACA_t \times 3 + \gamma_2 ArbSpread_{t-1} + \gamma_3 MACA_{t-3} \times ArbSpread_{t-1} + \varepsilon_t \]  

The dependent variable alpha (\( \hat{\alpha}_t \)) is out-of-sample forecast of alpha calculated in each month \( t \) according to the procedure described in the previous subsection. The first independent variable is Merger Arbitrage Capital Abundance – MACA. For every month \( t \), MACA is defined as \( \log \left( \frac{Aggr.M&A Fund Assets_{t-1}}{Aggr.M&A Value_t} \right) \). For a given month \( t \), the numerator of the ratio is calculated by adding assets under management for all U.S. focused, U.S. dollar denominated merger arbitrage hedge funds reporting to HFR/Tass databases in month \( t - 1 \). The denominator is obtained by adding the disclosed value of all merger deals (net of assumed liabilities) announced in month \( t \) where the target is U.S. firm.\(^{16}\) The ratio of the numerator to denominator represents the merger capital available as of the beginning of month \( t \) for investment per $1 of deals announced in month \( t \). We then take the natural log of this ratio. In the regression model we use the difference between MACA and its sample average – the difference enters the model with 3 month lag. The average is taken over the entire 1994 – 2010 period. The demeaning is necessary in order to interpret the regression intercept as the average value of alpha when independent variables are set equal to their respective time series averages. As defined the \( \log \left( \frac{Aggr.M&A Fund Assets_{t-1}}{Aggr.M&A Value_t} \right) \) does not equal zero in our sample and can only be equal zero if the aggregate funds under management equal aggregate value of M&A deals announced – a very unlikely outcome given the much larger size of aggregate M&A market relative to M&A hedge fund assets under management.\(^{17}\) In line with hypothesis 1, we expect a negative relationship between alpha and MACA.

\(^{16}\)If there are multiple bidders for the company we use the value of the first bid. Multiple bidders are defined as in Bates, Becher, and Lemmon (2008) and Bates and Lemmon (2003).

\(^{17}\)Both Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests indicate that MACA time series is time-stationary.
The second independent variable $\text{ArbSpread}_{q-1}$ is median arbitrage spread for friendly, cash-only deals announced in the previous calendar quarter and it measures potential unleveraged strategy profitability. Quarterly frequency is used instead of monthly frequency for median arbitrage spread because in some months the number of cash only and friendly M&A deals announced is zero or very small. This in turn creates discontinuities in the monthly median spread time series. Switching to a quarterly time period avoids the data issues associated with the monthly time series. As with MACA, the unit root tests indicate that median quarterly arbitrage spread variable is time-stationary. Thus for a given month $t$, $\text{ArbSpread}_{q-1}$ is the median arbitrage spread of cash only friendly deals announced during months $t-5$ to $t-3$. As stated above, to calculate arbitrage spread for a given deal we subtract target’s stock price one trading day after offer bid announcement from offer’s bid price and divide the difference by target’s stock price one trading day after offer bid announcement. In line with hypothesis 2, we expect direct relationship between the spread and alpha. The merger arbitrage strategy is unique among hedge fund strategies in that it allows such direct measurement of potential profitability. Just as with MACA variable we use de-meaned lagged median arbitrage spread in our regressions.\(^{18}\) Again, de-meaning allows one to interpret the intercept of Equation (3) as the value of merger arbitrage strategy alpha when the MACA and the median merger arbitrage spread variables are set equal to their respective time series averages.

We include the interaction between two variables to explore whether the impact of each variable is independent of the other. It is possible that the impact of capital abundance on strategy alpha is different in low and high profitability environments. Similarly, the impact of profitability on strategy returns may be different between periods of capital abundance and periods of capital scarcity. We estimate Equation (3) using OLS and report Newey and West (1987) 6-lag standard errors to account for serial correlation.\(^{19}\)

\(^{18}\)As defined previously, median arbitrage spread variable is the median calculated using a cross-section of arbitrage spreads at a point in time. To obtain de-meaned value of this variable in each quarter we subtract its time-series mean from the value of median arbitrage spread in that quarter.

\(^{19}\)The statistical significance of our results does not change substantially if instead we use 12 or 18 lags in computation of Newey-West standard errors.
4 Results and Discussion

Tables 2 and 3 report Equation (1) estimates for asset-weighted excess return and HFRIMAI excess return seven factor models, respectively. As reported by other studies, such as Block (2006), column 1 of each table shows that returns of merger arbitrage hedge funds are moderately exposed to equity risk. The results also show that excess returns are negatively related to interest rates and credit spreads. Again, this is not surprising given that the cost of leverage and entering into short positions are likely to be directly related to credit spreads and interest rates. Column 1 of each table also indicates that trend following variables appear to have small and statistically insignificant impact on excess returns in specifications that use HFRIMAI excess return and in specifications that use asset weighted excess return.\textsuperscript{20} We also find that in the 1994 – 2010 period the alpha (regression intercept) ranged between 30 and 40 basis points per month. The estimate of alpha is statistically significant in both specifications.

Columns 2 through 6 of Tables 2 and 3 investigate the changes in merger arbitrage strategy excess return exposure to seven risk factors over time. The sub-periods are based on sub-periods used by Fung, Hsieh, Naik, and Ramadorai (2008) and Naik, Ramadorai, and Stromqvist (2007) and reflect structural breaks in hedge fund risk exposures. In particular, prior to 2000 structural breaks correspond to Long Term Capital Management crisis in 1998 and collapse of NASDAQ in early 2000. Chow (1960) test identifies the same structural breaks in our data for both HFRIMAI and asset weighted excess return models. Post 2000, we used the methodology prescribed by Fung, Hsieh, Naik and Ramodarai to identify one structural break in late 2004, and another in early 2008 corresponding to the time of collapse of Bear Stearns.

In addition to changes in exposures to the seven risk factors over time, we find significant variation in alpha (i.e., the constant) as well. For example Table 2 shows that the alpha corresponding to the sub-period 10/1998 to 03/2000 (column 3 of Table 2) is 79 basis points

\textsuperscript{20}With exception of bond trend following factor, that is statistically significant in asset weighted excess return specification.
while the alpha corresponding to the sub-period 04/2000 to 12/2004 (column 4 of Table 2) is only 11 basis points. The alphas shown in Table 2 also indicate a declining trend. The alpha was statistically significant and ranged between 43 and 79 basis points per month in the 1990s (columns 2 and 3 of Table 2). Between 2000 and 2004 the alpha declined substantially to become small and statistically indistinguishable from zero (column 4). Then between 2005 and 2010 the alpha recovered somewhat and ranged approximately between 27 to 30 basis points per month, but has never reached its 1990s levels (columns 5 and 6 of Table 2). Similar results can be seen in Tables 3 as well, where alphas are computed based on excess returns of HFRIMAI.

The general trend of alphas shown in Tables 2 and 3 – an increase in the 1990s followed by a relatively sharp decline in the early 2000s, which is then followed by a recovery, albeit to levels lower than the ones observed in the late 1990s – is somewhat reflective of the trends of MACA and arbitrage spread shown in Figures 1 and 2. This correspondence in trends suggests that the evolution of MACA and arbitrage spread over time may help explain the changes in the alpha of merger arbitrage funds.

Following methodology outlined in the previous section, we estimate Equation (3) to examine the extent to which alphas of merger arbitrage funds can be explained by MACA and arbitrage spread. Table 4 presents the results of the regression. Again, we present results for alphas based on asset weighted excess returns of merger arbitrage funds in our sample (columns 1 to 5 of Table 4) and excess returns of HFRIMAI (columns 6 to 10 of Table 4).

Table 4 shows a statistically and economically significant relationship between MACA and alpha, and as expected the relationship is negative (Columns 2 and 7). An increase in MACA indicates greater competition between hedge funds that puts a downward pressure on returns in the merger arbitrage strategy. Table 4 also shows that, as expected, merger arbitrage spread has a strong positive relationship with alpha (Columns 3 and 8). Introduction of merger arbitrage spread does have an impact on MACA’s coefficient, such that magnitude of the coefficient
declines. However, even after the introduction of arbitrage spread, the coefficient for MACA is negative and economically and statistically significant. This result is not surprising as the sample correlation coefficient between MACA and median arbitrage spread is -0.44. It appears that a part of MACA’s effect on alpha when arbitrage spread is omitted from the model is driven by MACA’s negative impact on merger arbitrage profitability. This result seems to suggest that merger arbitrage spread acts as an important conduit or channel through which expansion in merger arbitrage capital lowers M&A strategy alpha. Overall, the signs and size of coefficients on MACA and median arbitrage spread lend support to our two hypotheses.

One can also gauge the relative importance of the merger arbitrage spread and MACA variables by comparing their betas or standardized coefficient estimates.\textsuperscript{21} Columns 5 and 10 of Table 4 report beta or standardized coefficients for estimates in column 3 and 8, respectively. Column 5 indicates that one standard deviation increase in MACA is associated with 0.13 standard deviation decline in monthly alpha. Similarly, one standard deviation increase in median arbitrage spread predicts 0.21 standard deviation increase in monthly alpha, indicating that effect of arbitrage spread exceeds the effect of MACA in absolute magnitude when both variables enter the model.

Next, we analyze the possibility that the effects of MACA and arbitrage spread on alpha may be interdependent by including an interaction variable between lagged MACA and lagged median arbitrage spread. As shown in Table 4, the interaction coefficient is positive and statistically significant (columns 4 and 9). This result suggests that the effect of arbitrage capital scarcity on alpha depends on the level of merger arbitrage spread. Similarly, the effect of changes in merger arbitrage spread on alpha depends on the level of MACA.

We explore the nature of interdependence between MACA and arbitrage spread and its impact on alpha. In particular we investigate how alpha varies in different MACA and merger arbitrage spread regimes. For purposes of our analysis we distribute our sample period into

\textsuperscript{21}A beta coefficient estimate represents the number of standard deviations by which the dependent variable changes in response to 1 standard deviation change in an independent variable.
four regimes. The matrix below shows the regimes,

<table>
<thead>
<tr>
<th>Spread Above Median</th>
<th>Spread Below Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>MACA Above Median</td>
<td>1</td>
</tr>
<tr>
<td>MACA Below Median</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>4</td>
</tr>
</tbody>
</table>

Regime 1 represents the market environment where both MACA and merger arbitrage spread are above their respective median values for the entire sample period. Thus Regime 1 includes all months where MACA and merger arbitrage spread of deals announced in that month is greater than the time series median of MACA and of merger arbitrage spread for the entire sample. Regime 2 includes months where MACA is above the sample median while arbitrage spread below the median; Regime 3 contains all observations characterized by MACA below the median and by arbitrage spread above the sample median; and Regime 4 represents periods where both MACA and arbitrage spreads are below their respective medians. The matrix above broadly captures all market environments that are potentially relevant to performance of merger arbitrage strategy.

Table 5 shows the number of months that fall into each regime and the average alpha for each regime. The table shows the negative relationship between MACA and arbitrage spread. For example, 70 out of the 173 months in our sample period fell into Regime 2 (above median MACA and below median arbitrage spread), while 52 months fell into Regime 3 (below median MACA and above median arbitrage spread). Thus, the results show that periods of relatively abundant (scarce) capital coincided with relatively low (high) arbitrage spreads. However, the negative correlation is not perfect. In a non-trivial number of months scarce arbitrage capital coincided with low merger arbitrage spreads – Regime 4 (N = 26); and relatively abundant arbitrage capital coincided with high merger arbitrage spreads – Regime 1 (N = 25). These results suggest that while relative supply of arbitrage capital is important to merger arbitrage profitability, other factors such as variation in merger completion risk over time have

\(^{22}\)For clarity, we do not use de-meaned values of MACA and median arbitrage spread in Table 5.
independent effect on merger arbitrage spread.

Second, Table 5 also shows that the impact of MACA and arbitrage spread strongly depends on market environment. Consider MACA first. In environments characterized by low profitability, i.e., relatively low arbitrage spread, an increase in MACA or arbitrage capital abundance sharply reduces alpha from about 40 to 60 basis points per month to levels that are close to zero (columns 3 and 6). In contrast, when arbitrage strategy profitability is high the change in capital abundance has practically no effect on alpha – it remains close to 60 basis points per month (columns 2 and 5). It appears that the negative impact of MACA on alpha is economically significant primarily in low profitability environments, but has no substantial effect in high profitability environments.

Similarly, the impact of arbitrage spread on alpha strongly depends on the abundance of arbitrage capital. We find that in environments characterized by relatively abundant arbitrage capital (high MACA) an increase in arbitrage spread (profitability) increases alpha from nearly zero to about 64 – 68 basis points per month. However, in environments characterized by scarce arbitrage capital, the alpha is positive and large even when arbitrage spread is relatively low. While the change in alpha in response to increase in arbitrage spread is positive, it is small and statistically insignificant (with p-values in excess of 0.30).

[Insert Table 5 here]

The results of reported in Tables 4 and 5 support the notion that expansion of supply of merger arbitrage capital relative to the value of M&A deals (i.e. increase in MACA) has resulted in the decline of merger arbitrage hedge funds’ excess returns and alphas over time. We also find that to some extent the effect of capital expansion works through decline in merger arbitrage strategy’s profitability. Adding merger arbitrage spread variable to the model reduces the impact of MACA on alpha.

The variation in MACA and the median arbitrage spread can together explain about 6% to 8% of variation in the merger arbitrage strategy alpha. However, we find that using MACA and arbitrage spread enables us to accurately predict out-of-sample alpha from the rolling window
Fung and Hsieh (2004) seven risk factor model without splitting the sample into sub-periods to account for shifts in systematic risk exposures.

To evaluate the ability of the model formulated in Equation (3) to predict alpha over time we first compute an out-of-sample alpha using Equation (1). As described in section 3.2 we estimate Equation (1) over a 24 month period ending a month before the month for which the alpha is being forecasted. To compute alpha for month $t$ we subtract the product of realized values of seven risk factors in month $t$ and seven factor loadings estimated over the previous 24 month of data from realized excess return ($r_t$) in month $t$. After computing the alpha for all months in our sample we use forecasted alpha as a dependent variable and estimate Equation (3) to obtain coefficients estimates for the 1994 – 2010 period. We then use these estimates, realized values of lagged MACA and realized values of lagged median arbitrage spread to predict out-of-sample monthly alpha for each sub-period identified in Table 2.

Recall that these sub-periods are based on structural breaks in systematic risk exposures that we have identified in our sample in section 4. We then compare the predicted out-of-sample mean alphas for each sub-period (predicted using estimates from Equation 3) to the sub-period in-sample alphas based on identified structural breaks. The in-sample predicted alphas are the same as the constants shown in Table 2, except for the first sub-period where the constant is recomputed for January 1996 through September 1998.$^{23}$

Figure 5 shows that the variation in MACA and in median arbitrage spread can help identify the same changes in alpha over time as the sub-period estimates of Fung and Hsieh (2004) seven factor model. The latter explicitly takes into account the structural shifts in systematic risk exposures of merger arbitrage strategy returns. The figure shows that the predicted out-of-sample alphas evolve in a way that is quite similar to period specific in-sample alphas (estimated constants from Table 2). In particular, we see a substantial decline in average alpha in 2000 – 2004 period (to about 10 basis points per month) relative to its 1990s level. After 2004, alpha recovers to about 30 to 40 basis points per month but never

$^{23}$Given that we use a 24 months of data in the rolling window regression, the first sub-period for which we can compute an out-of-sample predicted alpha begins January 1996.
catches up with its levels in the previous decade. The results reported in Figure 5 are also consistent with the evolution of MACA presented in Figure 1, which showed that prior to 2003 MACA exhibited an increasing trend and peaked around 2002. Similarly, the results in Figure 5 are also consistent with the evolution of arbitrage spread presented in Figure 2, which showed that merger arbitrage spreads were significantly greater prior to 2003 and bottomed out around 2003.

To explore robustness of the results reported in Tables 2 and 3, we have re-estimated the risk factor model using four factors of the Fung and Hsieh (2004) model and dropping trend following factors as in Jetley and Ji (2010). Similar to the results for the seven factor model, the four factor model also shows that excess returns of merger arbitrage hedge funds are exposed to equity risk; that increase in interest rates and credit spreads have a negative impact on returns and that estimated intercept (alpha) declines in 2000-2004 period to zero and recovers in post-2004 period but never catches up with its 1990s levels. Further, we use four factor 24-month rolling regression to generate out-of-sample alpha forecast. We re-estimate Equation (3) (alpha model) using the alternative alpha forecast and find that results reported in Tables 4 and 5 remain qualitatively the same.\textsuperscript{24}

In line with previous research, we address survivorship bias in our study by analyzing performance of all three types of funds: currently active, liquidated or funds that have stopped reporting. Because our sample contains funds that were active as of the end of the sample period (2010) as well as those that were liquidated or stopped reporting prior to that date (most of them in 2008) the results are unlikely to be affected by survivorship bias. Additionally, to test for possible impact of backfill bias we excluded observations on fund returns prior to date the fund joined the HFR and Tass databases, re-calculated asset weighted M&A strategy excess return and re-run the factor model and alpha analyses. The results were substantively unaffected. Lastly, to test if our results are driven by 2008 financial crisis we excluded monthly

\textsuperscript{24}Four factor model results are available upon request.
observations subsequent to December 2006. Again, the risk factor model and alpha results remained unaffected.

Taken as a whole, our results lend significant support to hypotheses 1 and 2 and are consistent with capacity constraint hypothesis. The results indicate that the decline in merger arbitrage hedge fund alpha seems to be driven by expansion of relative supply of merger arbitrage capital that increases the competition between merger arbitrageurs and at the same time significantly reduces merger arbitrage spread. Both factors appear to be driving recent decline in merger arbitrage hedge fund returns and alpha.

5 Conclusions

In this study we analyze a survivorship bias-free sample of merger arbitrage hedge funds over two decade period in an attempt to understand the reasons for the decline in returns and alpha that has been documented by prior studies. We begin by documenting a number of interesting facts about returns of merger arbitrage hedge funds and develop our testable hypotheses on the basis of these facts. The paper then explores the extent to which the decline in returns and alpha of merger arbitrage funds can be explained by strategy-wide factors such as changes in the demand and supply of arbitrage capital and by evolution of profitability of merger arbitrage strategy.

Among the facts that we document is a lack of persistence and convergence of merger arbitrage hedge fund returns over long horizon. Using multi-year horizon provides an opportunity to explore the impact of significant variation in the level of merger arbitrage spreads and arbitrage capital over time. We find that merger arbitrage hedge funds that reported returns in the top quartile during the 1994 – 2002 period, were not able to report top-quartile returns during 2003 – 2010 period. The decline in returns, the compression of return distribution and the inability of merger arbitrage hedge funds to report persistently high returns suggests that skill levels, in terms of having the ability to evaluate deal risk and deliver superior returns to investors, does not vary much across fund managers. Alternatively, even if there is a difference
in skill levels the declining merger arbitrage spread and its narrowing distribution does not enable the more skillful managers to distinguish themselves from less skillful ones. We also find that the lack of persistence and convergence of merger arbitrage hedge fund returns over time coincides with a significant expansion in merger arbitrage capital and corresponding decline in merger arbitrage spread. This observation leads us to a conjecture that the strategy wide factors may be critical to observed changes in merger arbitrage funds’ performance over time.

We expand on the previous studies of merger arbitrage performance that report economically and statistically significant excess returns related to merger arbitrage in the 1980s and 1990s. We contribute to the literature along two dimensions. First, we provide a novel way to measure capacity constraints and profitability of an arbitrage strategy. The nature of merger arbitrage provides an opportunity to measure both factors explicitly. The capacity of merger arbitrage strategy can be measured by comparing both the demand and supply of capital where demand is measured by the dollar value of M&A deals at any point in time, and supply is measured by assets under management of merger arbitrage funds at the same point in time. Unleveraged profit potential can be measured directly by arbitrage spread. Such measures of market capacity and potential profitability may not be possible for many other hedge fund strategies.

Second, we find that evolution in relative supply of capital and arbitrage spread can help explain the evolution of merge arbitrage strategy alpha over the last two decades. We find that increase in supply of arbitrage capital relative to the demand for merger arbitrage capital (i.e, volume of available M&A deals) decreases merger arbitrage strategy alpha, while an increase in arbitrage spread increases strategy alpha. The effect of arbitrage spread appears to be of greater magnitude than the effect of relative supply when both variables enter the alpha model. Further, the two variables are correlated-expansion of supply of arbitrage capital relative to volume of M&A deals coincides with declining arbitrage spreads in the last two decades. These results lend support to existence of significant capacity constraints in merger arbitrage strategy.
References


This figure reports the logarithm of the monthly ratio of assets under management to value of announced M&A deals between 1994 and 2010. For each calendar month the numerator is the sum of assets under management of U.S.-focused hedge funds whose assets are denominated in U.S. dollars as reported by HFR and Lipper Tass databases. The denominator is the sum of values of M&A bids announced in a given calendar month net of assumed liabilities as reported by Thomson ONE Banker database. We used only bids that, if completed, will result in change in control defined as increase in ownership by the bidder from less than 50% to more than 50%. Trend is estimated using locally weighted scatterplot smoothing. Sources: Hedge Fund Research, Inc., Lipper Tass, Thomson ONE Banker.
**Figure 2**

**Median quarterly arbitrage spread, 1994 - 2010**

This figure reports median arbitrage spread for 1994 - 2010 period. Median arbitrage spread is the median for friendly, cash-only control bids announced in a given quarter. Control bids are the bids that, if completed, will result in change in control defined as increase in ownership by the bidder from less than 50% to more than 50%. To calculate the arbitrage spread we subtract target’s stock price one trading day after offer bid announcement from the offer’s bid price and divide the difference by target’s stock price one trading day after offer bid announcement. For multiple bid auctions we use the first offer’s bid price and stock price one trading day after the day of the first bid announcement. Multiple bidders are defined as in Bates, Becher and Lemmon (2008) and Bates, Lemmon (2003). We remove outliers by excluding the top and the bottom 1% of merger arbitrage spread values. Trend is estimated using locally weighted scatterplot smoothing. Source: Thomson ONE Banker.
Figure 3
Distribution of average monthly raw hedge fund returns, 1994 - 2010

Figure 4

**Raw hedge fund returns, 1994 - 2010**

Figure 5
MACA and Arbitrage Spread as predictors of M&A arbitrage strategy alpha over time

This figure reports the comparison between alpha estimated using Fung and Hsieh (2004) 7-factor model and alpha predicted by MACA and merger arbitrage spread. Subperiod alphas are intercept estimates from asset weighted excess return regression on seven risk factors. Out of sample alpha is one month ahead forecast based on rolling 24 month regression of asset weighted excess return on seven factors. Predicted alpha is the prediction based on regression of out of sample alpha on MACA and median arbitrage spread reported in Table 4, column 4. Because data spanning 1/1994 - 12/1995 period is used to generate first alpha forecast, we compute out of sample alpha starting January 1996.
### Table 1

**Performance persistence among M&A arbitrage hedge funds, 1994 - 2010**

This table reports relative performance persistence among merger arbitrage hedge funds over 1994 - 2010 period. Performance is measured as an average raw monthly return. Each cell represents the number of hedge funds. N = 30. Funds formed prior to 2003 only. Sources: Hedge Funds Research Inc., Lipper Tass.

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<td>5</td>
<td><strong>1</strong></td>
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<tr>
<td><strong>Total</strong></td>
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<td>8</td>
<td>7</td>
<td>8</td>
<td>30</td>
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Table 2

Factor regressions for asset weighted M&A arbitrage strategy excess return. Seven factor model, 1994 - 2010


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<td>(5)</td>
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<td>S&amp;P500 index monthly return minus 1-month T-bill return</td>
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<td>0.142***</td>
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<td>0.0443**</td>
<td>0.164**</td>
<td>0.0787**</td>
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<td>(2.06)</td>
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<td>0.0576</td>
<td>0.0980*</td>
<td>0.0305*</td>
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<td>(0.83)</td>
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<td>(1.39)</td>
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***, ** and * indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.
Table 3
Factor regressions for HFRIMAI excess return. Seven factor model, 1994 - 2010


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<td>S&amp;P500 index monthly return minus 1-month T-bill return</td>
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<td>0.0646</td>
<td>0.0860**</td>
<td>0.176***</td>
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<td>(4.97)</td>
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<td>(1.22)</td>
<td>(2.62)</td>
<td>(5.08)</td>
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<td>Difference between the S&amp;P SmallCap 600 Index return and the S&amp;P 500 monthly returns</td>
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<td>0.124***</td>
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<td>(-0.15)</td>
<td>(-1.02)</td>
<td>(-2.43)</td>
<td>(-3.44)</td>
</tr>
<tr>
<td>Bond Trend-Following Factor (PTFSBD)</td>
<td>-0.00482</td>
<td>-0.000954</td>
<td>-0.0119</td>
<td>0.000163</td>
<td>0.00396</td>
<td>-0.0125</td>
</tr>
<tr>
<td></td>
<td>(-0.87)</td>
<td>(-0.19)</td>
<td>(-0.73)</td>
<td>(0.04)</td>
<td>(0.27)</td>
<td>(-1.37)</td>
</tr>
<tr>
<td>Currency Trend-Following Factor (PTFSFX)</td>
<td>0.00302</td>
<td>-0.000218</td>
<td>0.0214*</td>
<td>0.00685</td>
<td>0.00252</td>
<td>0.0112</td>
</tr>
<tr>
<td></td>
<td>(1.08)</td>
<td>(-0.08)</td>
<td>(1.76)</td>
<td>(1.10)</td>
<td>(0.47)</td>
<td>(0.91)</td>
</tr>
<tr>
<td>Commodity Trend-Following Factor (PTFSCOM)</td>
<td>-0.00420</td>
<td>-0.00870</td>
<td>-0.00437</td>
<td>-0.0221*</td>
<td>0.00375</td>
<td>-0.0220</td>
</tr>
<tr>
<td></td>
<td>(-0.80)</td>
<td>(-1.17)</td>
<td>(-0.82)</td>
<td>(-1.93)</td>
<td>(0.39)</td>
<td>(-1.55)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00380***</td>
<td>0.00516***</td>
<td>0.00891***</td>
<td>0.00134</td>
<td>0.00444**</td>
<td>0.00239***</td>
</tr>
<tr>
<td></td>
<td>(5.14)</td>
<td>(4.88)</td>
<td>(7.26)</td>
<td>(1.03)</td>
<td>(2.62)</td>
<td>(3.84)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.450</td>
<td>0.602</td>
<td>0.529</td>
<td>0.455</td>
<td>0.648</td>
<td>0.801</td>
</tr>
<tr>
<td>Number of observations</td>
<td>201</td>
<td>56</td>
<td>18</td>
<td>57</td>
<td>38</td>
<td>32</td>
</tr>
</tbody>
</table>

***, ** and * indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.
## Determinants of seven factor model alpha, 1996-2010

This table reports the regression of alpha on MACA and median arbitrage spread. Dependent variable (columns 1 to 5): alpha derived from Asset weighted M&A arbitrage strategy 7 factor excess return model, Dependent variable (columns 6 to 10): alpha derived from the 7 factor HFR Merger Arbitrage Hedge Fund Index (HFRIMAI) excess return model. For both models alpha are out of sample forecast based on rolling 24 month regressions. T-statistics in parentheses are based on Newey-West (1987) 6-lags standard errors. Beta or standardized coefficient represents the number of standard deviations by which the dependent variable changes in response to 1 standard deviation change in an independent variable. Beta coefficients in columns 5 and 10 are reported for estimates appearing in columns 3 and 8, respectively. De-meaned Merger Arbitrage Capital Abundance is defined as the logarithm of the ratio of aggregate M&A hedge fund assets in month t-1 to the aggregate value of M&A in month t minus its sample mean over 1994 - 2010 period. 3 - month lag is used as independent variable in the regressions. De-meaned Lagged Median (Average) Arbitrage Spread is median (average) spread for friendly, cash-only control bids announced in the previous quarter. Because data spanning 1/1994 - 12/1995 period is used to generate first out-of-sample alpha forecast 1994 and 1995 are excluded from estimation. Sources: Hedge Fund Research, Inc., Lipper Tass, Ibbotson Associates.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (t-stat. in parenthesis)</th>
<th>Coefficient (t-stat. in parenthesis)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.00335*** (3.36)</td>
<td>0.00405*** (3.97)</td>
</tr>
<tr>
<td>Lagged De-meaned Merger Arbitrage Capital Abundance (MACA)</td>
<td>-0.00170** (-2.76)</td>
<td>-0.00172** (-2.36)</td>
</tr>
<tr>
<td>Lagged De-meaned Median Arbitrage Spread</td>
<td>0.130*** (3.48)</td>
<td>0.125*** (3.22)</td>
</tr>
<tr>
<td>Lagged De-meaned MACA x Lagged De-meaned Median Arbitrage Spread</td>
<td>0.056** (2.17)</td>
<td>0.048* (1.73)</td>
</tr>
<tr>
<td>Adj. R-squared</td>
<td>-- 0.035 0.0679 0.0767</td>
<td>-- 0.0329 0.0601 0.0645</td>
</tr>
<tr>
<td>Number of observations</td>
<td>173 173 173 173</td>
<td>173 173 173 173</td>
</tr>
</tbody>
</table>

***, ** and * indicate statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.
Table 5

Merger arbitrage market environments and M&A strategy alpha. Seven factor model, 1996 - 2010

This table reports M&A strategy alpha in different merger arbitrage market environments between 1996 and 2010. Scarce (abundant) capital environment exists when MACA is below (above) its time series median, low (high) profitability environment exists when arbitrage spread is below (above) its time series median. N (months) represents the number of observations on alpha. Alpha is out of sample forecast obtained from rolling 24-month window regressions of HFRIMAI or asset weighted returns on the seven risk factors of Fung and Hsieh(2004). Sources:Hedge Fund Research, Inc., Lipper Tass, Ibbotson Associates, Thomson ONE Banker.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Excess asset weighted return model</th>
<th>Excess HFRIMAI return model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Arbitrage spread above its median</td>
<td>Arbitrage spread below its median</td>
</tr>
<tr>
<td>MACA above its median</td>
<td>0.639% (-0.010%)</td>
<td>0.031</td>
</tr>
<tr>
<td>(abundant arbitrage capital)</td>
<td>25 70</td>
<td></td>
</tr>
<tr>
<td>MACA below its median</td>
<td>0.616% 0.409%</td>
<td>0.339</td>
</tr>
<tr>
<td>(scarce arbitrage capital)</td>
<td>52 26</td>
<td></td>
</tr>
<tr>
<td>p-value for alpha equality test</td>
<td>0.941 0.017</td>
<td></td>
</tr>
</tbody>
</table>