Upside Potential of Hedge Funds as a Predictor of Future Performance*

Turan G. Bali[a], Stephen J. Brown[b], and Mustafa O. Caglayan[c]

ABSTRACT

This paper examines whether chasing past high returns has a rational basis for hedge fund investors. We measure upside potential based on the maximum monthly returns of hedge funds (*MAX*) over a fixed time interval, and show that *MAX* successfully predicts cross-sectional differences in future fund returns. Hedge funds with strong upside potential generate 0.70% per month higher average returns than funds with weak upside potential. After controlling for alternative risk and performance measures and a large set of fund characteristics, the positive link between *MAX* and future returns remains highly significant. Moreover, funds with strong upside potential have higher probability of survival, attract more capital, and are rewarded with higher fees. The results indicate that the market/macro-timing ability of hedge funds together with their extensive use of dynamic trading strategies is the source behind *MAX*'s predictive power.

Keywords: Hedge funds; upside potential; return predictability.

JEL Classification: G10, G11, C13.

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[a] Robert S. Parker Professor of Finance, McDonough School of Business, Georgetown University, Washington, D.C. 20057. Phone: (202) 687-3784, E-mail: turan.bali@georgetown.edu.

[b] Professor, Monash Business School, Melbourne, Vic. 3145 Australia, and Emeritus Professor of Finance, NYU Stern School of Business, New York, NY 10012. Phone: +61 3 9903 4953 E-mail: stephen.brown@monash.edu.

[c] Associate Professor of Finance, College of Business, Florida International University, Miami, FL 33199. Phone: (305) 348-8430, E-mail: mustafa.caglayan@fiu.edu.

1. Introduction

The hedge fund industry has been playing an important role in investment decisions of a wide variety of investors for the past two decades. Although the hedge fund industry has grown rapidly and there has been an increasing interest to develop complex measures to identify best performers in different market conditions, there is still evidence of hedge fund investors' naive tendency to chase past high returns. Fund flows have been found to be highly related to past returns in the hedge fund universe.[1] Moreover, the concentration of the financial press on funds that have been extaordinarily successful, with very high past returns might be evidence of a significant behavioral bias (salience) on the part of both the financial press and of investors who take this writing seriously. What we have found, and for the first time, that there may be a rational basis for this return chasing behavior. In this paper we propose a new measure of upside potential and test if future performance of hedge funds is related to their upside potential. We quantify upside potential based on the maximum monthly returns of hedge funds (*MAX*) over a fixed time interval, and test whether *MAX* succesfully predicts the cross-sectional differences in future fund returns. Our results suggest that the concentration on past high returns might not be irrational after all. We find that, our measure for past high return, *MAX*, is indeed associated positively with high future returns. We attribute this finding to the fact that standard performance metrics do not account for positive skewness in returns as a relevant characteristic of performance. Once accounted for, we find that behavioral bias towards high past returns is indeed material as it contributes to standard performance measures in predicting future returns.

Our measure of upside potential, *MAX*, is also motivated by the empirical observation that the hedge fund return distributions exhibit significant departures from normality. Specifically, we show that the historical distribution of monthly hedge fund returns is skewed, peaked around the mode, and has fat-tails. Moreover, we find that hedge funds' frequent utilization of dynamic trading strategies with nonlinear payoffs is reflected in their non-normal return distributions. It is crucial to note that while standard performance measures do not account for nonlinearities in payoffs, the upside measure, *MAX*, not only captures option-like features of hedge fund payoffs, but also succesfully predicts the cross-sectional differences in future performance.

We find that *MAX* obtained from the right tail of the empirical return distribution is highly persistent as well. The estimated historical *MAX* successfully predicts future *MAX* values and thus the maximum return observed over a period of time does say something about both the future upside potential and the future performance of individual funds. Investors pay high fees for hedge funds that have exhibited strong upside potential with the expectation that this behavior will be repeated in the future. This strong cross-sectional persistence in the right tail of the hedge fund return distribution supports upside potential

[1] In a testimony before the U.S. House of Representatives Committee on Financial Services dated on March 13, 2007, Stephen Brown, David S. Loeb Professor of Finance from NYU Stern School of Business, acknowledges that "operational risk does not mediate the naïve tendency of investors to chase past returns" in his speech entitled *Hedge Funds and Systematic Risk in the Financial Markets*. Fund flows chasing past returns are also clearly documented in published academic papers including Brown, Goetzmann, Liang, and Schwarz (2008, 2012).

as a robust predictor of future performance and also justifies a rational basis for a strong relation between upside potential and net fund flows.

The results from our empirical analyses also indicate that funds with strong upside potential attract more capital, and they are rewarded with higher fees and have higher probability of survival. We find that upside potential is related to funds' market-timing ability and superb knowledge of financial markets, proxied by their frequent use of dynamic trading strategies with derivatives, short-selling, and leverage.

We investigate whether the extremely large positive returns observed over the past six months to 24 months (i.e., upside potential measured over different length of periods) predict the future performance of hedge funds via alternative tests. First, we form quintile portfolios by sorting individual hedge funds based on their maximum monthly return (*MAX*) over a specified period, where quintile 1 contains the hedge funds with the lowest *MAX* (weak upside potential) and quintile 5 contains the hedge funds with the highest *MAX* (strong upside potential). For the *MAX* generated over the past 12 months, we find that the next month average return difference between quintiles 5 and 1 is 0.70% per month and highly statistically significant, indicating that hedge funds in the highest *MAX* quintile generate 8.4% more annual returns compared to funds in the lowest *MAX* quintile. After controlling for the Fama-French-Carhart four factors of market, size, book-to-market, and momentum, as well as Fung and Hsieh (2001) five trend-following factors on currency, bond, commodity, short-term interest rate, and stock index, we find the return spread between the high-*MAX* and low-*MAX* funds (nine-factor alpha) remains positive, at 0.47% per month, and highly significant. More importantly, the results also indicate that the positive relation between *MAX* and future fund returns remains strong 18 months into the future; funds with strong upside potential outperform funds with weak upside potential, not just for one month, but for 1.5 years into the future in risk-adjusted terms, if an investor were to have an investment horizon or a lock-up period of one year or longer.

Next, we provide results from the bivariate portfolios of *MAX* and alternative proxies of risk and performance. Specifically, after controlling for the past average returns, standard deviation, *MIN* (downside risk), Sharpe ratio, alpha, appraisal ratio, incentive fee, and net fund flows in bivariate sorts, we find that *MAX* remains a significant predictor of future fund returns. The univariate and bivariate portfolio-level analyses clearly indicate that upside potential, proxied by *MAX*, is a strong, persistent predictor of future performance containing information orthogonal to alternative measures such as the alpha, appraisal ratio, and Sharpe ratio.

In addition to these portfolio-level analyses, we run fund-level cross-sectional regressions to control for multiple effects simultaneously. In multivariate Fama-MacBeth (1973) regressions, we control for lagged return, standard deviation, *MIN*, the Sharpe ratio, the alpha, the appraisal ratio, fund flow, and a large set of fund characteristics (age, size, management/incentive fee, redemption period, minimum investment amount, lockup, and leverage). Even after this large set of fund characteristics and alternative risk and performance measures are simultaneously controlled for, the positive link between *MAX* and future returns remains highly significant. We also perform subsample analyses and find that these regression results are robust across different sample periods and states of the economy. Thus, both Fama-MacBeth regressions and portfolio-level analyses provide strong corroborating evidence for an economically and statistically significant positive relation between *MAX* and future hedge fund returns.

Hedge funds have various trading strategies. Some willingly take direct market exposure and risk (directional strategies), some try to minimize market risk altogether (non-directional strategies), and some try to diversify market risk by taking both long and short diversified positions (semi-directional strategies). After classifying hedge funds into these three groups, we test whether the predictive power of *MAX* changes among different hedge fund investment styles. The results indicate that the predictive power of *MAX* gradually increases as we move from the least directional strategies to the most directional strategies. We obtain the highest predictive power of *MAX* for the directional strategies. Funds employing directional strategies have a higher *MAX* on average and they employ a wide variety of dynamic trading strategies and make extensive use of derivative products and leverage compared to non-directional funds. In fact, our results show that for hedge funds with no derivatives and low leverage usage, the next month return and alpha differences between high-*MAX* and low-*MAX* funds are not significant. On the other hand, the return/alpha spreads between high-*MAX* and low-*MAX* funds are positive, bigger in magnitude and highly significant for funds with high leverage and derivatives usage compared to the full sample results.

In an alternative analysis related to funds' leverage and derivatives usage, we also examine if hedge funds are able to time fluctuations in the equity market and macroeconomic fundamentals. Henriksson-Merton (1981) pooled panel regression results show that directional funds have significant timing ability compared ton non-directional funds. Directional funds willingly take direct exposure to financial and macroeconomic risk factors, relying on their market- and macro-timing ability to generate superior returns. Since these are funds with dynamic trading strategies that frequently use derivatives and leverage that are highly exposed to market risk and economic uncertainty, timing the switch in economic trends is essential to their success. Hence, our main finding of a stronger link between *MAX* and future returns for directional funds can be attributed to the evidence of the superior market- and macro-timing abilities of these directional hedge fund managers. In fact, when we run the market-timing test at the fund level and sort funds according to their market-timing coefficients, we find that the next month return and alpha spreads between high-*MAX* and low-*MAX* funds are not significant for the funds with low market-timing ability. On the other hand, the return/alpha spreads between high-*MAX* and low-*MAX* funds are positive, bigger in magnitude and highly significant for the funds with high market-timing ability compared to the full sample results.

Lastly, we find that the high-*MAX* funds have higher probability of survival, are able to attract larger capital inflows and charge higher management and incentive fees compared to low-*MAX* funds. These results suggest that investors are indeed willing to pay higher fees and invest more in the high-*MAX* funds with the expectation of receiving large positive returns in the future. Our finding that the high-*MAX* funds with strong upside potential are rewarded with higher fees, and their flows, as a percentage of assets, are significantly greater explains also why there may be a rational basis for a strong performance–flow relation in the hedge fund universe.

This paper proceeds as follows. Section 2 provides a literature review. Section 3 describes the data and variables. Section 4 presents extensive out-of-sample empirical evidence. Section 5 investigates whether hedge funds with strong upside potential have higher probability of survival, attract more capital, and are rewarded with higher fees. Section 6 examines the predictive power of *MAX* for directional, semi-directional, and non-directional hedge funds and performs market- and macro-timing tests. Section 7 concludes the paper.

2. Literature Review

In this paper, our main objective is to examine if return chasing behaviour has a rational basis for hedge fund investors. In that respect, we check whether superior future performance of hedge funds is related to a measure of upside potential. Our main findings suggests that this upside measure complements other standard measures of performance in predicting the cross-sectional variation in hedge fund returns. Hence, this paper contributes in a significant way to the growing literature on the cross-sectional determinants and predictors of hedge fund performance.[2] As we show *MAX*'s predictive ability is linked to funds' derivatives and leverage usage as well as funds' market-timing ability, this study is also related to the literature on the market-timing ability of hedge funds. Following the pioneering work of Treynor and Mazuy (1966), a large number of studies have investigated the timing ability of professional fund managers. With a few exceptions, most of the earlier work focuses on mutual funds and finds little evidence of market-timing ability. Only recently, a few studies have investigated whether individual hedge funds have the ability to time fluctuations in the equity market, aggregate market liquidity, and macroeconomic fundamentals.[3]

One of the challenges facing performance measurement in the hedge fund context is that, as Jagannathan and Korajczyk (1986) show, funds with access to derivative instruments and dynamic portfolio strategies can construct portfolios that show artificial timing ability when no true timing ability exists. This can be accomplished through the purchase of out-of-the-money call options (or dynamic trading strategies that accomplish the same ends). Such strategies give rise to positive timing coefficients (in the sense of Treynor and Mazuy (1966)) and an elevated *MAX* relative to the benchmark. However, the elevated *MAX* that results from this portfolio strategy comes at the cost of a negative alpha. Alternatively, funds can appear to generate spurious alpha and elevated Sharpe ratios by engaging in short volatility strategies. Goetzmann, Ingersoll, Spiegel, and Welch (2007) show that, by constructing portfolios whose payoff is concave relative to the benchmark (an attribute of short volatility), managers can attain a Sharpe ratio in excess of the benchmark and a positive alpha.[4] However, an attribute of such strategies with

[2] A partial list includes Fung and Hsieh (1997, 2000, 2001, 2004), Ackermann, McEnally, and Ravenscraft (1999), Mitchell and Pulvino (2001), Agarwal and Naik (2000, 2004), Bali, Gokcan, and Liang (2007), Fung et al. (2008), Patton (2009), Aggarwal and Jorion (2010), Bali, Brown, and Caglayan (2011, 2012, 2014), Cao, Chen, Liang, and Lo (2013), Patton and Ramadorai (2013), Agarwal, Arisoy, and Naik (2016), and Agarwal, Ruenzi, Weigert (2016).
[3] See, e.g., Cao, Chen, Liang, and Lo (2013) and Bali, Brown, and Caglayan (2014).
[4] Strictly speaking, this result requires the benchmark to be lognormally distributed. In private correspondence, Jonathan Ingersoll has shown that the same result follows for a quite general distribution of the benchmark, so long as the payoff is strictly concave relative to the benchmark.

concave payoff is that the *MAX* will be less than or equal to that of the benchmark. Therefore, the critical criteria for investors should be to select fund managers who can generate positive and significant alphas (Sharpe ratios) as well as high *MAX* at the same time. In this context, *MAX* can be viewed as a complementary measure to alpha and Sharpe ratio to detect truly good performance. In other words, truly robust performance should manifest itself in both elevated alpha (Sharpe ratio) and a high *MAX* relative to the benchmark.

There is a substantial literature that addresses the challenge of determining an appropriate performance measure where managers have access to derivative positions and dynamic portfolio strategies that mimic such positions. Jagannathan and Korajczyk (1986) suggest factoring in the value of the implied options in measuring the performance of managers who employ dynamic trading strategies. Agarwal and Naik (2004) suggest augmenting factors with out-of-the-money put and call factors in constructing abnormal performance metrics, while Goetzmann et al. (2007) suggest a manipulation-proof performance metric (MPPM) based on the certainty equivalent of the dynamic trading strategy payoffs. These metrics deviate from standard measures when benchmark returns take on extreme values. However, hedge fund investors have access to only limited disclosure on trading and positions, and in many cases the only information available to investors is a limited history of past monthly returns.[5] Therefore, it is a challenge to estimate these aforementioned metrics with precision when the only information available to investors is a small number of monthly hedge fund returns. Rather than seeking an adjustment to standard measures of performance that accommodate the nonlinear characteristic of hedge fund payoffs, our approach in this paper is to rank performance both by standard measures of performance and by *MAX*.

3. Data and Variables

In this section, we first describe the hedge fund database, fund characteristics, and their summary statistics. Then we provide definitions of key variables used in the cross-sectional predictability of future fund returns. Finally, we present the standard risk factors used in the estimation of the risk-adjusted returns (alphas) of *MAX*-sorted portfolios.

3.1. Hedge fund database

This study uses monthly hedge fund data from the Lipper Trading Advisor Selection System (TASS) database. In the database, we initially have information on 19,746 defunct and live hedge funds. However, among these 19,746 funds, many are listed multiple times, since they report returns in different currencies, such as the US dollar, euro, pound sterling, and Swiss franc. These funds are essentially not separate funds but a single fund with returns reported on a currency-converted basis. In addition, typically a hedge fund has an offshore fund and an onshore fund, following the exact same strategy. Therefore, naturally, the returns for all these funds are highly correlated. However, the TASS database assigns a

[5] In the TASS hedge fund database, the median reported life of 19,746 hedge funds (and 11,099 U.S. dollar denominated funds) is only 60 months. Excluding the first 12 to 24 months of data to address incubation bias issues in hedge fund databases (Fung and Hsieh (2000)) leaves very few observations of monthly returns necessary to estimate these models.

separate fund reference number to each onshore and offshore fund and to each of the funds reporting in different currencies, treating these funds as separate individual funds. To distinguish between different share classes (of the same fund) and other actual funds and to avoid duplicate funds (and hence returns) in our analyses, we first omit all non-US dollar-based hedge funds from our sample. That is, we keep in our database only hedge funds reporting their returns in US dollars. Next, if a hedge fund has both an offshore fund and an onshore fund with multiple share classes, we keep the fund with the longest return history in our database and remove all the other share classes of that particular fund from our sample. This way, we make sure that each hedge fund is represented only once in our database. After we remove all non-US dollar-based hedge funds and hedge funds with multiple share classes, our database contains information on 11,099 distinct, non-duplicated hedge funds for the period January 1994 to December 2014, 8,684 of which are defunct funds and the remaining 2,415 of which are live funds.

The TASS database, in addition to reporting monthly returns (net of fees) and monthly assets under management (AUM), provides information on certain fund characteristics, including management fees, incentive fees, redemption periods, minimum investment amounts, and lockup and leverage provisions. Section I of the Online Appendix further discusses the TASS database and provides a detailed section on how we handle potential data bias issues, such as survivorship bias, backfill bias, and multiperiod sampling bias (e.g., Brown, Goetzmann, Ibbotson, and Ross (1992), Fung and Hsieh (2000), Liang (2000), and Aggarwal and Jorion (2010)). Panel A of Table I in the Online Appendix provides summary statistics on the numbers, returns, AUM, and fee structures for the sample of 11,099 hedge funds. Panel B of Table I reports the cross-sectional mean, median, standard deviation, minimum, and maximum values for certain hedge fund characteristics for the sample period January 1994 – December 2014.

We also report the distributional moments of hedge fund returns. For each fund in our sample from January 1994 to December 2014, we compute the volatility, skewness, and excess kurtosis of monthly hedge fund returns and then test whether these high-order moments are significantly different from zero based on the time-series distribution of hedge fund returns. Panel C of Table I in the Online Appendix shows that among 8,010 hedge funds that have a minimum of 24 monthly return observations, all of them have significant volatility at the 10% level or better. In addition, 2,888 funds exhibit positive skewness and 5,122 funds exhibit negative skewness. Among the funds with positive (negative) skewness, 50.3% (63.8%) are statistically significant at the 10% level. Finally, the majority of hedge funds (7,118 funds) exhibit positive excess kurtosis and among these funds, 74.8% are statistically significant at the 10% level. We also conduct the Jarque-Bera (JB) normality test and the last column of Panel C in Table I shows that 70.3% of the funds in our sample exhibit significant JB statistics, rejecting the null hypothesis of normality at the 10% level.[6]

[6] For 66.0% (60.0%) of the funds in our sample, the JB statistics are significant at the 5% (1%) level, rejecting the null hypothesis of normality.

3.2. Variable definitions

In the literature, the performance of hedge funds has been tested by traditional measures such as the capital asset pricing model (CAPM) alpha, the Sharpe ratio, and the appraisal ratio. In addition to these risk-adjusted return measures, incentive fees and fund flows are also analyzed as a measure behind superior fund performance. Separate from the previous work, this paper quantifies upside potential of hedge funds based on the maximum monthly returns of funds over a fixed time interval and examines if this measure can predict superior future fund performance.

MAX: Motivated by the empirical evidence that the distribution of hedge fund returns exhibits significant departures from normality, and that hedge funds' frequent utilization of dynamic trading strategies with nonlinear payoffs is reflected in their non-normal return distributions; we use five alternative measures of extreme hedge fund returns in the right tail (*MAX*) to check the predictive power of upside potential over future fund returns. The variables *MAX6*, *MAX9*, *MAX12*, *MAX18*, and *MAX24* represent the maximum monthly hedge fund returns over the past six, nine, 12, 18, and 24 months, respectively.

Control variables: We use a large set of fund characteristics, past returns, volatility, and risk-adjusted return measures to test whether the predictive power of *MAX* is driven by these variables. Specifically, we use *Size*, measured as monthly AUM in billions of dollars; *Age*, measured as the number of months in existence since inception; *Flow*, measured as the change in AUM from the previous month to the current month, adjusted with fund returns and scaled with the previous month's AUM;[7] *IncentFee*, measured as a fixed percentage fee of the fund's annual net profits above a designated hurdle rate; *MgtFee*, measured as a fixed percentage fee of AUM, typically ranging from 1% to 2%; *MinInvest*, measured as the minimum initial investment amount that the fund requires from its investors to invest in a fund; *Redemption*, measured as the minimum number of days an investor needs to notify a hedge fund before the investor can redeem the invested amount from the fund; *DLockup*, measured as the dummy variable for lockup provisions (equal to one if the fund requires investors to not withdraw initial investments for a pre-specified term, usually 12 months, and zero otherwise); and *DLever*, measured as the dummy variable for leverage (equal to one if the fund uses leverage and zero otherwise).

In addition to this large set of fund characteristics, in our analyses, we also control for alternative risk and performance measures, including the one-month-lagged return (*LagRet*); the past 12-month average return (*AVRG*); the past 12-month standard deviation (*STDEV*); the past 24-month Sharpe ratio (*SR*), computed as the past 24-month average excess return divided by the past 24-month standard deviation; the past 24-month alpha; and the past 24-month appraisal ratio (*AR*) obtained from the nine-factor model of Fama and French (1993), Carhart (1997), and Fung and Hsieh (2001):

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[7] Fund flow is defined as $\{\text{Assets}_t - [(1 + \text{Return}_t) \cdot \text{Assets}_{t-1}]\}/\text{Assets}_{t-1}$.

$$R_{i,t} = \alpha_i + \beta_{1,i} \cdot MKT_t + \beta_{2,i} \cdot SMB_t + \beta_{3,i} \cdot HML_t + \beta_{4,i} \cdot MOM_t + \beta_{5,i} \cdot FXTF_t + \beta_{6,i} \cdot BDTF_t + \beta_{7,i} \cdot CMTF_t + \beta_{8,i} \cdot IRTF_t + \beta_{9,i} \cdot SKTF_t + \varepsilon_{i,t} \quad (1)$$

where MKT_t, SMB_t, HML_t, and MOM_t are the four factors of Fama and French (1993) and Carhart (1997) and $FXTF_t$, $BDTF_t$, $CMTF$, $IRTF$, and $SKTF$ are the five trend-following factors of Fung and Hsieh (2001). The unsystematic (or fund-specific) risk of fund *i* is measured by the standard deviation of $\varepsilon_{i,t}$ in Eq. (1), denoted $\sigma_{\varepsilon,i}$. The appraisal ratio (*AR*) is used to determine the quality of a fund's investment picking ability. It compares the fund's alpha (α_i) to the portfolio's unsystematic risk: $AR_i = \alpha_i / \sigma_{\varepsilon,i}$.

MIN: In addition to a large number of control variables described above, we use three alternative measures of extreme hedge fund returns in the left tail (*MIN*) to proxy for downside risk. The variables *MIN12*, *MIN24*, and *MIN36* represent the negative of the minimum monthly hedge fund returns over the past 12, 24, and 36 months, respectively.[8] The original maximum likely loss values are negative since they are obtained from the left tail of the empirical return distribution, but the downside risk measure, *MIN*, used in our analyses is defined as –1 times the maximum likely loss. Therefore, we expect a positive relation between *MIN* and hedge fund returns, that is, the higher the downside risk, the higher the expected return should be (see, e.g., Bali, Gokcan, and Liang (2007)).

3.3. Risk factors

We rely on the widely accepted nine factors when computing the risk-adjusted return of *MAX*-sorted hedge fund portfolios. Specifically, we use the market, size, book-to-market, and momentum factors of Fama and French (1993) and Carhart (1997) as well as the five trend-following factors of Fung and Hsieh (2001) for currenies, bonds, commodities, short-term interest rates, and stock indexes. The monthly returns on the four Fama-French-Carhart factors are obtained from Kenneth French's online data library. The five trend-following factors of Fung and Hsieh (2001)—FXTF, BDTF, CMTF, IRTF, and SKTF—are obtained from David Hsieh's online data library. Section II of the Online Appendix provides descriptions of these nine factors used in our empirical analyses.

4. Empirical Results

In this section, we investigate if *MAX* predicts the future performance of individual hedge funds. First, we perform a univariate portfolio-level analysis of *MAX*. Second, we examine the significance of cross-sectional persistence in *MAX*. Third, we report the results from conditional bivariate portfolios of *MAX* and alternative performance measures. Fourth, we investigate the predictive power of *MAX* and the

[8] The *MIN* variable can be viewed as a measure of Value-at-Risk (VaR) that determines how much the value of a portfolio could decline over a given period of time with a given probability as a result of changes in market prices. For example, if the given period of time is one day and the given probability is 1%, the VaR measure would be an estimate of the decline in the portfolio value that could occur with a 1% probability over the next trading day. In other words, if the VaR measure is accurate, losses greater than the VaR measure should occur less than 1% of the time.

traditional performance measures (alpha, the appraisal ratio, and the Sharpe ratio) using independent bivariate portfolios. Fifth, we investigate the predictive power of *MAX* controlling for *MIN*, the measure for downside risk. Sixth, we present the results from Fama-MacBeth cross-sectional regressions controlling for a large number of variables simultaneously. Seventh, we investigate the long-term predictive power of *MAX*. Finally, we summarize our results from a battery of robustness checks.

4.1. Univariate portfolio analysis of MAX

For each month from January 1995 to December 2014, we form quintile portfolios by sorting hedge funds based on their maximum monthly returns over the past six, nine, 12, 18, and 24 months (*MAX6*, *MAX9*, *MAX12*, *MAX18*, and *MAX24*, respectively), where quintile 1 contains the hedge funds with the lowest *MAX* values and quintile 5 contains the hedge funds with the highest *MAX* values. Panel A of Table 1 shows the average *MAX* values and the next-month average returns on *MAX*-sorted portfolios. The last two rows in Table 1, Panel A, display the average monthly return and nine-factor alpha differences between quintiles 5 and 1.

Panel A of Table 1 shows that, for each *MAX* measure, moving from quintile 1 to quintile 5, the next month average return on the *MAX*-sorted portfolios increases monotonically, leading to an economically and statistically significant return spread between the high-*MAX* and low-*MAX* quintiles. Specifically, for *MAX6*-sorted portfolios, the average return increases from 0.10% to 0.91% per month, yielding a monthly average return difference of 0.81% between quintiles 5 and 1, with a Newey-West (1987) *t*-statistic of 3.85. This result indicates that hedge funds in the highest *MAX* quintile (with strong upside potential) generate about 9.72% more in annual returns compared to funds in the lowest *MAX* quintile (with weak upside potential). Similar return spreads are obtained for other measures of *MAX* as well. The average return difference between quintiles 5 and 1 is 0.75% per month (*t*-stat. = 3.79) for *MAX9*-sorted portfolios, 0.70% per month (*t*-stat. = 3.48) for *MAX12*-sorted portfolios, 0.56% per month (*t*-stat. = 3.01) for *MAX18*-sorted portfolios, and 0.51% per month (*t*-stat. = 2.71) for *MAX24*-sorted portfolios.

We also check whether the significant return spread between the high-*MAX* and low-*MAX* funds is explained by the four Fama-French-Carhart factors of market, size, book-to-market, and momentum, as well as Fung and Hsieh's five trend-following factors on currencies, bonds, commodities, short-term interest rates, and stock indexes.[9] As shown in the last row of Table 1, Panel A, the nine-factor alpha difference between quintiles 5 and 1 is positive and significant for all measures of *MAX*. Specifically, the risk-adjusted return spread between quintiles 5 and 1 is 0.55% per month (*t*-stat. = 2.87) for *MAX6*-sorted portfolios, 0.50% per month (*t*-stat. = 2.70) for *MAX9*-sorted portfolios, 0.47% per month (*t*-stat. = 2.44) for *MAX12*-sorted portfolios, 0.39% per month (*t*-stat. = 2.10) for *MAX18*-sorted portfolios, and 0.36% per

[9] At an earlier stage of the study, we did control for the fixed income exposures of hedge funds as well as potential exposure to emerging markets. Including the bond market factors (based on the default spread and the term spread) from Fung and Hsieh's (2004) model as well as an emerging market equity factor in our risk adjustment model produced very similar findings.

month (t-stat. = 2.04) for *MAX24*-sorted portfolios. These results suggest that, after well-known factors are controlled for, the return spread between high-*MAX* and low-*MAX* funds remains positive and significant.

Next, we investigate the source of the raw and risk-adjusted return differences between the high-*MAX* and low-*MAX* portfolios: Is it due to outperformance by high-*MAX* funds, underperformance by low-*MAX* funds, or both? For this, we compare the economic and statistical significance of the average returns and the nine-factor alphas of quintile 1 versus quintile 5.[10]

Panel B of Table 1 shows that, for *MAX12*-sorted portfolios, the average return and the nine-factor alpha of quintile 1 are 0.09% and –0.01% per month, with t-statistics of 1.08 and –0.20, respectively, indicating that the average raw and risk-adjusted returns of the low-*MAX* funds are economically and statistically insignificant. On the other hand, the average return and the nine-factor alpha of quintile 5 are 0.79% and 0.46% per month, with t-statistics of 3.13 and 2.25, respectively, implying economically large and statistically significant positive returns for the high-*MAX* funds. These results provide evidence that the positive and significant return spread between the high-*MAX* and low-*MAX* funds is due to outperformance by the high-*MAX* funds with strong upside potential, but not due to underperformance by the low-*MAX* funds with weak upside potential.

4.2. Persistence of MAX

The maximum return over the past 12 months (*MAX*) documented in the first column of Panel B of Table 1 is for the portfolio formation month and not for the subsequent month over which we measure average returns. Institutional investors as well as wealthy individual investors would like to pay high incentive and management fees for hedge funds that have exhibited strong upside potential (i.e., high *MAX* values) in the past in the expectation that this behavior will be repeated in the future. Table 2 investigates this issue by presenting the average month-to-month portfolio transition matrix. Specifically, Panel A of Table 2 presents the average probability that a hedge fund in quintile i (defined by the rows) in one month will be in quintile j (defined by the columns) in the subsequent 12 months. If upside potential, proxied by *MAX*, is completely random, then all the probabilities should be approximately 20%, since a high or a low *MAX* value in one month should say nothing about the *MAX* values in the following 12 months. Instead, all the top-left to bottom-right diagonal elements of the transition matrix exceed 30%, illustrating that the maximum return over the past 12 months is highly persistent, even after a 12-month gap is established between the lagged and lead *MAX* variables. Of greater importance, this persistence is especially strong for the extreme *MAX* quintiles. Panel A of Table 2 shows that for the 12-month-ahead persistence of *MAX*, hedge funds in quintile 1 (quintile 5) have a 59.5% (58.2%) chance of appearing in the same quintile next year. These results indicate that the estimated historical *MAX* successfully predicts future *MAX* values and hence the maximum return observed over the past 12 months does say something about the future upside potential and superior future performance of individual funds.

[10] Instead of repeating the full set of analyses for all measures of *MAX*, we present the remainder of our results based on *MAX12* starting with Panel B of Table 1 (and onward). For notational simplicity, the maximum return over the past 12 months is hereafter denoted *MAX*.

A slightly different way to examine the persistence of *MAX* is to look at the fund-level cross-sectional regressions of *MAX* on lagged predictor variables. Specifically, for each month in the sample, we run a regression across funds of the 12-month-ahead *MAX* on the current *MAX* and current fund characteristics:

$$MAX_{i,t+12} = \lambda_{0,t} + \lambda_{1,t} \cdot MAX_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+12}\,, \tag{2}$$

where $MAX_{i,t}$ is the maximum monthly return of fund *i* in month *t* over the past 12 months (from month *t* – 11 to *t*), $MAX_{i,t+12}$ is the 12-month-ahead *MAX* of fund *i* (from month *t* + 1 to *t* + 12), and $X_{i,t}$ denotes the past return, volatility, and other characteristics of fund *i* in month *t*. Specifically, $X_{i,t}$ includes *MIN*, the past 24-month nine-factor alpha (*Alpha*), the past 12-month average return (*AVRG*), the past 12-month standard deviation (*STDEV*), the past one-month return (*LagRet*), and fund characteristics *Size*, *Age*, *Flow*, *IncentFee*, *MgtFee*, *MinInvest*, *Redemption*, *DLockup*, and *DLever*.

Panel B of Table 2 reports the average cross-sectional coefficients from these regressions and the Newey-West adjusted *t*-statistics. In the univariate regression of the 12-month-ahead *MAX* on the current *MAX*, the average slope coefficient is positive, quite large, and extremely statistically significant and the average *R*-squared value of 28.5% indicates substantial cross-sectional predictive power. In other words, hedge funds with extreme positive returns over the past 12 months also tend to exhibit similar features in the following 12 months. When the aforementioned 14 control variables are added to the regression, the coefficient of the lagged *MAX* remains large and highly significant (last row in Table 2, Panel B). In univariate regressions, besides *MAX,* of the remaining 14 variables, it is *MIN*, *Alpha*, the standard deviation (*STDEV*), the past 12-month average return (*AVRG*), the past one-month return (*LagRet*), and the incentive fee (*IncentFee*) that contribute most to the predictability of 12-month-ahead *MAX*. The remaining eight variables all have univariate *R*-squared values of less than 3% in univariate regressions. Overall, the results in Table 2 indicate that the persistence of upside potential, proxied by *MAX*, is not captured by size, age, fee structure, risk/liquidity attributes, and/or other characteristics of individual funds.

4.3. Conditional bivariate portfolio analysis

In this section, we perform a conditional bivariate portfolio test for *MAX* by controlling for the following measures: the past 12-month average return (*AVRG*), the past 12-month standard deviation (*STDEV*), the past 24-month Sharpe ratio (*SR*), the past 24-month nine-factor alpha, the past 24-month appraisal ratio (nine-factor *AR*) defined in Eq. (1), incentive fees, and fund flows.[11]

[11] To obtain a clear picture of the composition of the univariate *MAX*-sorted portfolios, Section III of the Online Appendix presents the average portfolio characteristics for the hedge funds in the *MAX*-sorted quintiles. Table II of the Online Appendix shows that the high-*MAX* funds exhibit higher average 12-month returns, higher 12-month standard deviations, higher past one-month returns, higher incentive fees, higher management fees, larger fund flows, lower minimum investment amounts, a lower redemption period, and more frequent use of dynamic trading strategies with derivatives and leverage, which may enable them to possess better market-timing and macro-timing abilities.

To perform this test, in Table 3, quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds first based on each control variable (namely, *AVRG*, *STDEV*, the Sharpe ratio, alpha, the appraisal ratio, incentive fees, and fund flows). Then, within each control variable-sorted portfolio, hedge funds are further sorted into sub-quintiles based on their *MAX*. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* within each control variable-sorted portfolio and quintile 5 is the portfolio of hedge funds with the highest *MAX* within each control variable-sorted portfolio. In each column of Table 3, the top panel reports the average *MAX* in each quintile and the lower panel reports those same quintiles' average returns for next month. The last two rows in Table 3 show the monthly average return differences and the nine-factor alpha differences between quintile 5 (high-*MAX* funds) and quintile 1 (low-*MAX* funds).

A notable point in Table 3 is that moving from the low-*MAX* to the high-*MAX* quintile, the next-month average return on *MAX*-sorted portfolios increases monotonically after all other risk and performance measures are controlled for. Specifically, we find the average return difference between quintiles 5 and 1 to be 0.44% per month with a *t*-statistic of 3.02 after controlling for the past 12-month average return, 0.69% per month (*t*-stat. = 5.71) after controlling for the past 12-month standard deviation, 0.67% per month (*t*-stat. = 3.39) after controlling for the Sharpe ratio, 0.57% per month (*t*-stat. = 3.18) after controlling for the nine-factor alpha, 0.69% per month (*t*-stat. = 3.46) after controlling for the appraisal ratio, 0.68% per month (*t*-stat. = 3.37) after controlling for incentive fees, and 0.68% per month (*t*-stat. = 3.55) after controlling for fund flows. In addition, as shown in the last row of Table 3, the nine-factor alpha differences between quintiles 5 and 1 are all positive, ranging from 0.29% to 0.68% per month, and all are statistically significant, with *t*-statistics well above 2.00.

These results provide strong evidence that, after alternative risk and performance measures and a large set of risk factors are controlled for, the return difference between the high-*MAX* and low-*MAX* funds remains positive and highly significant. Hence, we conclude that *MAX* is a robust measure of upside potential with strong incremental predictive power over future fund returns even after accounting for well-known measures of past performance such as the alpha, appraisal ratio, and Sharpe ratio.

4.4. MAX vs. Alpha

We now investigate the predictive power of *MAX* and the traditional performance measures (alpha, appraisal ratio, and Sharpe ratio) using independent bivariate portfolios. Table 4 presents the results from independently sorted 5×5 bivariate portfolios of *MAX* and Alpha. Within all Alpha quintiles, moving from the low-*MAX* to the high-*MAX* quintile, the next-month average return on *MAX*-sorted portfolios increases monotonically. In the same manner, the row labeled "Average" which presents the next-month returns of *MAX* quintile portfolios averaged across the Alpha quintiles, illustrates that the next month returns increase monotonically from low-*MAX* to high-*MAX* quintiles as well. After controlling for the nine-factor alpha, we find the raw return and alpha spreads between the high-*MAX* and low-*MAX* quintiles to be economically large, 0.69% and 0.54% per month, respectively, and highly statistically significant, with *t*-statistics of 3.69 and 2.79, respectively. More importantly, within all Alpha quintiles, the average return and alpha spreads between the high-*MAX* and low-*MAX* quintiles are also positive and highly significant, without exception (see the last two columns of Table 4).

Similar results are obtained for the nine-factor alpha, controlling for *MAX*. Table 4 shows that, within all *MAX* quintiles, moving from the low- to the high-Alpha quintile, the next-month average return on Alpha-sorted portfolios increases monotonically. The column labeled "Average" presents the next-month returns of the Alpha quintile portfolios averaged across the *MAX* quintiles. After *MAX* is controlled for, the raw return and alpha spreads between the high-Alpha and low-Alpha quintiles are economically large, 0.54% and 0.62% per month, respectively, and highly significant, with *t*-statistics of 6.35 and 8.47, respectively. In addition, within all *MAX* quintiles, the average return and alpha spreads between the high-Alpha and low-Alpha quintiles are also positive and highly significant, without exception (see the last two rows of Table 4). These results provide strong evidence that controlling for alpha (*MAX*) does not affect the significant predictive power of *MAX* (alpha) on future fund returns, reinforcing our interpretation of *MAX* as a complementary measure to alpha.[12] In other words, *MAX* and alpha have some distinct features in explaining the cross-sectional variation in future hedge fund returns and their predictive power is not subsumed by the existence of the other. Thus, investors need to focus on funds that generate both positive significant alpha and high *MAX* simultaneously for superior fund performance in the future.

In order to further highlight the importance of high alpha and high *MAX* in detecting future superior performance, we next report the average raw and risk-adjusted returns of the corner portfolios from 5×5 independent sorts of *MAX* and alpha, along with their Newey–West *t*-statistics in parentheses.

	Average Raw Returns			**Risk-Adjusted Returns**	
	Low MAX	*High MAX*		*Low MAX*	*High MAX*
Low Alpha	–0.48	0.52	*Low Alpha*	–0.59	0.20
	(–4.18)	(1.77)		(–6.13)	(0.78)
High Alpha	0.29	0.94	*High Alpha*	0.20	0.70
	(2.74)	(3.58)		(1.63)	(3.25)

The left panel above shows that the average return of the high-Alpha and high-*MAX* portfolio is significantly positive and the largest in economic magnitude among the 25 portfolios of *MAX* and alpha (see Table 4), at 0.94% per month (*t*-stat. = 3.58).[13] On the other hand, the average return of the low-Alpha and low-*MAX* portfolio is not only significantly negative, but also the lowest among the 25 portfolios of *MAX* and alpha, at –0.48% per month (*t*-stat. = –4.18).

As expected, the average returns of the low-Alpha and high-*MAX* portfolio and the high-Alpha and low-*MAX* portfolio are positive, but their performances are lower than the high-Alpha and high-*MAX*

[12] As discussed in Section 4.8 ("Robustness Check"), we provide the results from independently sorted 5×5 bivariate portfolios of *MAX* and the appraisal/Sharpe ratios as well. We find that controlling for the appraisal/Sharpe ratio (*MAX*) does not affect the significant predictive power of *MAX* (appraisal/Sharpe ratio) on future fund returns, implying that, in addition to their similar features, *MAX* and the traditional performance measures have some distinct characteristics and hence their predictive power is not subsumed by one another's.

[13] Another explanation consistent with this result is that by choosing funds with the greatest upside potential, one is able to avoid downside risk and for this reason is bound to increase alpha (see, e.g., Brown, Fraser, and Liang (2008)).

portfolio: 0.52% per month (t-stat. = 1.77) for the low-Alpha and high-*MAX* portfolio and 0.29% per month (t-stat. = 2.74) for the high-Alpha and low-*MAX* portfolio. We also test the statistical significance of the average return differences between the high-*MAX* and high-Alpha portfolio and the remaining three portfolios and find that the performance of the high-*MAX* and high-Alpha portfolio is significantly higher than the performances of the low-Alpha and low-*MAX*, low-Alpha and high-*MAX*, and high-Alpha and low-*MAX* portfolios.[14]

The right panel above replicates the same analyses based on the risk-adjusted returns of the corner portfolios from 5×5 independent sorts of *MAX* and alpha. Supporting our earlier findings, the nine-factor alpha of the high-Alpha and high-*MAX* portfolio is significantly positive and the highest in economic terms, 0.70% per month (t-stat. = 3.25), whereas the nine-factor alpha of the low-Alpha and low-*MAX* portfolio is negative, very large in magnitude, and statistically significant, –0.59% per month (t-stat. = –6.13). A notable point in the right panel is that the nine-factor alphas of the low-Alpha and high-*MAX* and the high-Alpha and low-*MAX* portfolios are positive but statistically insignificant. This shows that only high-Alpha and high-*MAX* funds can generate positive and significant risk-adjusted returns, and one needs to focus only on this category when selecting funds for superior future returns. In fact, as further supporting evidence, we find that the risk-adjusted performance of the high-*MAX* and high-Alpha portfolio is significantly higher than the risk-adjusted performances of the low-Alpha and low-*MAX*, low-Alpha and high-*MAX*, and high-Alpha and low-*MAX* portfolios.[15]

Overall, these results provide evidence that the managers of hedge funds with high Alpha and high *MAX* are the best performers, whereas the managers of hedge funds with low Alpha and low *MAX* are the worst performers. Hence, we conclude that, in combination with alpha, *MAX* provides a robust measure of performance that does not only capture the option-like payoffs of hedge funds, but also predicts the cross-sectional variation in future hedge fund returns.

4.5. MAX vs. MIN

In this section, we check whether the left-tail of the returns distribution, *MIN*, is also a strong predictor of the cross-sectional differences in hedge fund returns and whether *MIN* subsumes the predictive power of *MAX*. We first investigate the predictive power of *MIN* as a measure of downside risk in a univariate portfolio setting. For each month from January 1995 to December 2014, we form quintile portfolios by sorting individual hedge funds based on the negative of the minimum monthly return over the past 12, 24, and 36 months (*MIN12*, *MIN24*, and *MIN36*, respectively), where quintile 1 contains the hedge funds with the lowest *MIN* and quintile 5 contains the hedge funds with the highest *MIN*. Table III of the Online Appendix shows that the average return difference between quintiles 5 and 1 is 0.31% per

[14] The corresponding t-statistics from testing the null hypotheses that the average return on the high-*MAX* and high-Alpha portfolio equals the average returns on the low-Alpha and low-*MAX*, low-Alpha and high-*MAX*, and high-Alpha and low-*MAX* portfolios are 6.78, 2.51, and 2.70, respectively.

[15] The corresponding t-statistics from testing the null hypotheses that the nine-factor alpha on the high-*MAX* and high-Alpha portfolio equals the nine-factor alphas on the low-Alpha and low-*MAX*, low-Alpha and high-*MAX*, and high-Alpha and low-*MAX* portfolios are 6.65, 2.84, and 2.01, respectively.

month (t-stat. = 1.79) for *MIN12*-sorted portfolios, 0.41% per month (t-stat. = 2.34) for *MIN24*-sorted portfolios, and 0.49% per month (t-stat. = 2.88) for *MIN36*-sorted portfolios. As shown in the last row of Table III, the nine-factor alpha spread is positive but statistically insignificant for *MIN12*-sorted portfolios, whereas the nine-factor alpha spreads are positive and significant for *MIN24*- and *MIN36*-sorted portfolios. The results indicate that, among the three measures of downside risk, *MIN36* performs the best in terms of predicting cross-sectional variation in future returns, suggesting that *MIN36* provides a better characterization of left-tail risk compared to *MIN12* and *MIN24*.[16]

Next, we assess the predictive power of *MAX* and *MIN* using bivariate portfolios. Table 5 presents the results from independently sorted 5×5 bivariate portfolios of *MAX* and *MIN*. Within all *MIN* quintiles, moving from the low-*MAX* to the high-*MAX* quintile, the next-month average return on *MAX*-sorted portfolios increase monotonically. In the same manner, the row labeled "Average" which presents the next-month returns of *MAX* quintile portfolios averaged across the *MIN* quintiles, demonstrates that the next month returns increase monotonically from low-*MAX* to high-*MAX* quintiles as well. After controlling for *MIN*, we find the raw return and alpha spreads between the high-*MAX* and low-*MAX* quintiles are economically large, 0.85% and 0.77% per month, respectively, and highly statistically significant, with t-statistics of 6.12 and 5.16, respectively. More importantly, within all *MIN* quintiles, the average returns and alpha spreads between the high-*MAX* and low-*MAX* quintiles are also positive and highly significant, without exception (see the last two columns of Table 5).

Table 5 shows that, after controlling for *MAX*, however, there is no significantly positive link between *MIN* and future returns. In fact, controlling for *MAX* in independently sorted bivariate portfolios, we find a negative albeit insignificant relation between *MIN* and hedge fund returns; the average return and alpha spreads between the high-*MIN* and low-*MIN* quintiles are, respectively, –0.44% and –0.23% per month, with t-statistics of –1.56 and –1.43. Overall, the results indicate that, compared to *MIN*, *MAX* is a much stronger and more robust predictor of the cross-sectional differences in hedge fund returns.

4.6. Fama-MacBeth cross-sectional regressions

We now examine the cross-sectional relation between *MAX* and future returns at the individual fund level using Fama-MacBeth regressions. We present the time-series averages of the slope coefficients from the regressions of one-month-ahead hedge fund excess returns on *MAX* and a large set of control variables. The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables, on average, have non-zero premia. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot MAX_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+1}, \tag{3}$$

[16] Hence, we present the remainder of our results based on *MIN36* starting with Table 5 (and onward). For notational simplicity, the minimum return over the past 36 months is hereafter denoted *MIN*.

where $R_{i,t+1}$ is the excess return of fund *i* in month *t* + 1, $MAX_{i,t}$ is the maximum monthly return of fund *i* in month *t* over the past 12 months (from month *t* – 11 to *t*), and $X_{i,t}$ denotes a large set of fund characteristics such as the past returns, volatility, and risk-adjusted return measures of fund *i* in month *t*. Specifically, $X_{i,t}$ includes the following fund characteristics: *Size*, *Age*, *Flow*, *IncentFee*, *MgtFee*, *MinInv*, *Redemption*, *DLockup,* and *DLever*. In addition to these characteristics, $X_{i,t}$ includes *MIN*, the one-month-lagged fund returns (*LagRet*), the past 12-month average return (*AVRG*), the past 12-month standard deviation (*STDEV*), the past 24-month Sharpe ratio (*SR*) computed as the past 24-month average excess return divided by the past 24-month standard deviation, and the interaction term between the Sharpe ratio and *MAX*. In alternative regression specifications, we replace the Sharpe ratio with the nine-factor alpha and the appraisal ratio, estimated using the past 24 months of data.[17]

Table 6 presents the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions for the full sample period January 1995 to December 2014. The Newey-West-adjusted *t*-statistics are given in parentheses. We first investigate the cross-sectional relation between *MAX* and future fund returns without taking into account fund characteristics, the lagged return, lagged volatility, and the lagged risk-adjusted return. Consistent with our earlier findings from the univariate portfolio analysis, Regression (1) in Table 6 provides evidence of a positive and highly significant relation between *MAX* and future fund returns. The average slope from the monthly univariate regressions of one-month-ahead returns on *MAX* alone is 0.042 with a *t*-statistic of 3.52.

To determine the economic significance of this average slope coefficient, we use the average values of *MAX* in the quintile portfolios. Panel B of Table 1 shows that the difference in *MAX* values between average funds in the first and fifth quintiles is 14.21% per month (14.21% = 15.88% – 1.67%). If a fund were to move from the first to the fifth quintile of *MAX*, what would be the change in that fund's expected return? The average slope coefficient of 0.042 on *MAX* in Table 6 represents an increase of $(0.042)\cdot(14.21\%) = 0.60\%$ per month in the average fund's expected return for moving from the first to the fifth quintile of *MAX*. This result is similar to our earlier finding of a 0.70% per month return difference between the high-*MAX* and low-*MAX* funds from the univariate portfolio analysis reported in Table 1, Panel B.

After confirming a significantly positive link between *MAX* and future returns in univariate Fama-MacBeth regressions, we now control for *MIN*, lagged return, lagged volatility, lagged risk-adjusted returns (alpha and Sharpe/appraisal ratios), the interaction term between the risk-adjusted returns and *MAX*, and all fund characteristics simultaneously and test if *MAX* remains a strong predictor of future returns. Regression (2) in Table 6 shows that the average slope on *MAX* is 0.037, with a *t*-statistic of 2.78, implying that, after *MIN*, a large set of fund characteristics, risk factors, and alternative performance measures are controlled for, the positive relation between *MAX* and future hedge fund returns remains highly significant.

[17] At an earlier stage of the study, in addition to the past 24-month alpha and Sharpe/appraisal ratios, we used the past 12-month and 36-month alpha and Sharpe/appraisal ratios in our regression analyses and found similar results.

The average slope of 0.037 represents an economically significant increase of 0.53% per month in the average fund's expected return for moving from the first to the fifth quintile of *MAX*, controlling for everything else. Regressions (3) and (4) in Table 6 show that replacing the Sharpe ratio with the nine-factor alpha and the appraisal ratio does not change the significant predictive power of *MAX*.

In Table 6, although the average slope coefficients on the Sharpe ratio, alpha, and appraisal ratio are all positive and significant, the average slope coefficient on *MAX* continues to be positive and significant in each separate regression as well. More importantly, the average slope coefficients on the interaction terms between the risk-adjusted returns and *MAX* (i.e., SR×*MAX*, Alpha×*MAX*, and AR×*MAX*) are all positive and significant in each regression specification, suggesting that *MAX* is a complementary (not substitute) measure to alternative risk-adjusted performance measures, and *MAX* in combination with the Sharpe ratio, alpha, and appraisal ratio provides a robust measure of upside potential that accounts for nonlinearities in payoffs. The significantly positive average slopes on the interaction terms also indicate that the performance of the high-*MAX* and high-alpha funds remains significantly higher than the performance of the low-alpha and low-*MAX* funds after controlling for a large set of risk factors and fund characteristics in a multivariate Fama-MacBeth setting, confirming our earlier results from bivariate portfolio tests.

Another notable point in Table 6 is that the average slope coefficients of the control variables are consistent with earlier studies. Regressions (2) to (4) in Table 6 show that the average slopes on the one-month-lagged fund returns (*LagRet*) and the past 12-month average return (*AVRG*) are positive and highly significant. Consistent with the findings of Bali, Brown, and Caglayan (2012), the average slopes on the standard deviation of fund returns (*STDEV*) are also positive and statistically significant. In addition, in Regression (2), in line with the findings of Titman and Tiu (2011), the average slope on the Sharpe ratio is again positive and significant. Also, consistent with our findings from the bivariate portfolios of *MAX* and *MIN* in Table 5, the average slopes on *MIN* are negative but statistically insignificant. In sum, despite the fact that past return, past volatility, and past risk-adjusted return measures of individual hedge funds are found to be significant predictors of future returns, the significantly positive link between *MAX* and future fund returns remains highly significant in all regression specifications, suggesting that *MAX* is a strong predictor of future hedge fund performance.

Another interesting observation that comes out of Table 6 is that the incentive fee variable has a positive and significant coefficient in monthly Fama-MacBeth regressions, even when other fund characteristics are added to the regression equation (e.g., Brown, Goetzmann, and Ibbotson (1999)). As in previous results, however, the significance of incentive fees does not diminish the predictive power of *MAX* on future hedge fund returns. One last noteworthy point from Table 6 is that the minimum investment amount, the redemption period, and the dummy for lockup variables, which are used by Aragon (2007) to measure the illiquidity of hedge fund portfolios, also have positive and significant average slope coefficients. This suggests that funds that use lockup and other share restrictions that enable them to invest in illiquid assets earn higher returns in succeeding months, an outcome that coincides with Aragon's findings. However, even the significance of these liquidity variables does not alter or reduce the predictive power of *MAX* over hedge fund returns.

4.7. Long-term predictive power of MAX

We think that upside potential of hedge funds should be a relatively durable attribute. Hence, *MAX* is expected to predict fund performance over horizons that are significantly longer than a month. Our empirical analyses have thus far focused on one-month-ahead predictability. However, from a practical standpoint, it would make sense to investigate the predictive power of *MAX* for longer investment horizons, since some investors and hedge fund managers may prefer holding periods or investment horizons longer than one month. More importantly, the lock-up period for hedge fund investors changes from three months to a year. Hence, it is important to determine if *MAX* predicts the cross-sectional variation in one-quarter- to one-year-ahead returns of individual hedge funds.

In this section, we first focus on quarterly and annual returns and examine the long-term predictive power of *MAX* based on the univariate quintile portfolio analysis. Panel A of Table 7 reports one- to eight-quarter-ahead returns for *MAX*-sorted quintile portfolios. The average quarterly return difference between quintiles 5 and 1 is 2.05% per quarter (t-stat. = 3.39) at quarter t+1, 1.51% (t-stat. = 2.87) at quarter t+2, 1.32% (t-stat. = 2.82) at quarter t+3, 1.20% (t-stat. = 2.58) at quarter t+4, 1.09% (t-stat. = 2.50) at quarter t+5, and 1.13% (t-stat. = 2.80) at quarter t+6. The last row in Table 7 Panel A shows that the nine-factor alpha spreads between quintiles 5 and 1 are also positive and statistically significant from one quarter to six quarters. The last two columns of Table 7 Panel A show continuing statistical significance for the seven- and eight-quarter-ahead return spreads as well; however, the corresponding alpha spreads are statistically insignificant, indicating that the predictive power of *MAX* lasts up to six quarters (or 1.5 years) into the future.

Since the lock-up period for hedge fund investors is generally one year, we further investigate the predictive power of *MAX* for one-year-ahead returns. For this, in each quarter of our sample, we form univariate quintile portfolios of *MAX* and then compute one-year-ahead returns of the quintile portfolios as the cumulative returns of t+1, t+2, t+3, and t+4 quarters. We find that the one-year-ahead average return difference (or the four-quarter cumulative return difference) between quintiles 5 and 1 is positive and highly significant, 6.98% per annum with a t-statistic of 4.06. Similarly, the one-year-ahead nine-factor alpha difference is also positive, 6.16% per annum, and highly significant with a t-statistic of 2.46.[18]

In addition, we examine the one-year-ahead predictive power of *MAX* using non-overlapping samples and rebalancing portfolios annually. Over the 20-year period from January 1995 to December 2014, we form quintile portfolios of *MAX* once a year and then compute one-year-ahead returns of the quintile portfolios. The results from annual rebalancing and non-overlapping samples indicate that the one-year-ahead average return difference between quintiles 5 and 1 is 7.33% per annum (t-stat. = 4.99) and the nine-factor alpha difference is 3.63% per annum (t-stat. = 2.10).

[18] Because of four-quarter overlapping samples, the standard errors of the four-quarter cumulative average return and alpha differences are computed following Hodrick (1992).

Lastly, we examine the long-term predictive power of *MAX* via Fama-MacBeth cross-sectional regressions as well. Table 7 Panel B reports the average slope coefficients from the three-month-ahead and twelve-month-ahead hedge fund excess returns (separately) on *MAX* with and without control variables. In both univariate and multivariate regression settings, the average slope coefficient on *MAX* is always positive and significant, confirming the positive significant relation between *MAX* and long-term future hedge fund returns even after a large set of fund characteristics, risk factors, and alternative performance measures are simultaneously controlled.

Overall, the results from both the univariate portfolio tests and the Fama-MacBeth cross-sectional regressions provide evidence that the positive relation between *MAX* and future fund returns is not just a one-month affair. The predictive power of *MAX* remains strong more than one year into the future; funds with a higher *MAX* outperform funds with a lower *MAX*, not just for one month into the future, but for as long as 1.5 years into the future in risk-adjusted terms. This is an important finding for hedge fund investors with investment horizons or lock-up periods around one year or longer.

4.8. Robustness check

In this section, we perform a wide variety of tests examining the robustness of our findings and provide results from these tests in the Online Appendix. Section IV and Tables IV and V of the Online Appendix provide a detailed analysis of the interaction between *MAX* and volatility and show that controlling for volatility does not affect the significant predictive power of *MAX* on future fund returns. Section V and Tables VI and VII of the Online Appendix provide the results from independently sorted 5×5 bivariate portfolios of *MAX* and the appraisal/Sharpe ratios. The results show that controlling for the appraisal/Sharpe ratio (*MAX*) does not affect the significant predictive power of *MAX* (appraisal/Sharpe ratio) on future fund returns, suggesting that *MAX* is a good complementary measure to appraisal ratio and Sharpe ratio in detecting superior future fund performance. That is, *MAX* and Sharpe ratio and appraisal ratio have some distinct features in explaining the cross-sectional variation in future hedge fund returns and their predictive power is not subsumed by the existence of the other. Sections VI and VII and Tables VIII to X of the Online Appendix present evidence of a positive and significant link between *MAX* and future fund returns under alternative scenarios. Specifically, the main results hold for subsample periods, including expansionary and contractionary periods (see Online Appendix Table VIII). In addition, the results indicate that the predictive power of *MAX* is not driven by outliers in returns (see Online Appendix Table IX). Interestingly however, at the same time, the extreme returns of hedge funds contain significant information as well (see Online Appendix Table X) in terms of their ability to predict future hedge fund returns. Lastly, Table XI of the Online Appendix shows that *MAX* contains persistent, significant information about future upside potential that is orthogonal to the standard measures of performance as it has low correlation with alpha, appraisal ratio, and Sharpe ratio.

5. Upside Potential, Probability of Fund Survival, and Investors' Demand

In this section, we test whether hedge funds with strong upside potential have higher probability of survival, attract more capital, and are rewarded with higher fees.

5.1. Upside potential and hedge fund survival

In an effort to reinforce our interpretation of *MAX* as a robust measure of upside potential to detect superior future performance, in this section we investigate the link between fund survival and *MAX* using logit regressions. If *MAX* truly captures superior fund performance, it should also be positively related to fund survival, as fund failures are most of the time associated with prior significant negative returns. To this hypothesis, we run cross-sectional regressions of short-term and long-term future fund survival on *MAX* with and without control variables, including *MIN*, lagged returns, standard deviations, average returns, the Sharpe ratio, the interaction term between the Sharpe ratio and *MAX*, age, size, flow, management fees, incentive fees, the redemption period, the minimum investment amount, lockup, and leverage structures. Table 8 reports the average intercept and slope coefficients and the corresponding Newey-West *t*-statistics from the Fama-MacBeth cross-sectional logit regressions of one-month-, three-month-, and twelve-month-ahead hedge fund survival (measured as a dummy variable taking the value of one if the fund is in existence, or zero if the fund is deceased) on *MAX* with and without control variables.[19] In Panel A Table 8, where the dependent variable is next-month survival, the average slope coefficient on *MAX* is positive and highly significant in both the univariate and multivariate regressions, suggesting that *MAX* is positively related to fund survival, supporting our view of *MAX* as a robust measure to detect superior fund returns. More importantly, in Panels B and C of Table 8, we obtain similar statistically significant average slope coeffieints on *MAX*, when we use three-month- and twelve-month-ahead fund survival as the dependent variable in Fama-MacBeth logit cross-sectional regressions, suggesting that the positive relation between *MAX* and fund survival persists one year into the future.

Specifically, in Panel A of Table 8, in the univariate regression, the slope coefficient of 0.034 on *MAX* (with a *t*-statistics 5.94) indicates if a fund were to move from the first quintile (low-*MAX* quintile with an average *MAX* of 1.67%) to the fifth quintile (high-*MAX* quintile with an average *MAX* of 15.88%) as illustrated in Panel B of Table 1, the probability of survival for this fund would increase by 48.3% [(15.88 – 1.67)×0.034 = 48.3%]. Similarly, in the multivariate setting, after controlling for all fund characteristics, risk factors, and other performance measures, we find the magnitude of the slope coefficient on *MAX* and its corresponding Newey-West *t*-statistic to both increase to 0.051 and 6.42, respectively. In

[19] Since the dependent variable is a zero-one dummy variable taking the value of one if the fund is in existence, or zero if the fund is deceased, we need to make sure that we have good representation of deceased funds in our regression analyses. Although the TASS started to report returns of deceased funds in 1994 (hence the reason why we start all of our analyses from 1994), the number of deceased funds in the sample is very low in the early years. In fact, between 1994 and 2001, the average number of funds deceased per month is only 9.23. Only after 2002, the average number of funds deseased per month increases to acceptable levels (between 2002 and 2014, the average number of funds deceased per month is 50.48) such that we can obtain meaningful regression estimates from our logit cross-sectional regressions. Therefore, for this specific analysis on fund survival and *MAX*, we restrict our sample from January 2002 to December 2014.

fact, the slope coefficient of 0.051 on *MAX* indicates a 33% (0.051×6.5% = 33%) probability of survival for a typical fund with an average *MAX* measure of 6.5% in our sample after controlling all fund charactreristics, risk factors, and other performance measures (the average *MAX* measure of 6.5% is calculated as the average *MAX* measure of the five quintiles reported in Panel B of Table 1). These results indicate a significantly positive relation between *MAX* and future fund survival, reinforcing our measure of MAX as a robust measure of upside potential capable of detecting superior future fund performance.

5.2. Do investors prefer high-MAX funds?

Our results show that *MAX* has significant predictive power over future hedge fund returns. Thus, sophisticated investors may consider past *MAX* values as an alternative indicator for their future investment decisions. To determine whether investors account for differences in upside measures, we test if they are indeed willing to pay higher fees for funds with a high *MAX*.

As shown in Table II of the Online Appendix, the average management and incentive fees of individual funds increase monotonically when moving from quintile 1 to 5 in the univariate *MAX*-sorted portfolios. Specifically, the average management fee increases monotonically from 1.34% for the low-*MAX* funds to 1.58% for the high-*MAX* funds. Similarly, the average incentive fee increases monotonically from 12.9% for the low-*MAX* funds to 17.9% for the high-*MAX* funds. Consistent with these results at the portfolio level, the multivariate cross-sectional regressions of hedge fund fees on *MAX* and control variables, reported in Panels A and B of Table 9, produce consistently positive and highly significant average slope coefficients on *MAX*, indicating a strong positive link between *MAX* and fund fees after controlling for past fund performance and other fund-specific characteristics.

To test the hypothesis that high-*MAX* funds also attract greater capital flows, we examine the cross-sectional relation between *MAX* and the one-month-ahead net flows into the fund. Specifically, we sort individual hedge funds into quintile portfolios based on their *MAX* values and then calculate the average one-month-ahead net flows to funds in each quintile. Although not tabulated here to save space, the results indicate that the average net monthly flow, as a percentage of assets, is 52 basis points greater for the high-*MAX* funds than for the low-*MAX* funds. The difference between the net monthly flows of high-*MAX* and low-*MAX* funds is also highly significant, with a *t*-statistic of 3.69.

We also run multivariate Fama-MacBeth regressions to check if this strong predictive relation between *MAX* and fund flows remains intact after controlling for individual fund characteristics, past performance, and risk/liquidity attributes. The multivariate regressions reported in Panel C of Table 9 produce a positive and highly significant average slope coefficient on *MAX*, indicating a strong positive link between *MAX* and the one-month-ahead net flows into the fund after controlling for past fund performance and other fund-specific characteristics.

Overall, the results indicate that the ability of high-*MAX* funds to produce higher returns motivates them to charge higher management and incentive fees to their clients, compared to low-*MAX* funds. In addition, high-*MAX* funds attract more capital (higher net inflows). In sum, the findings in Table 9 show that funds with a high *MAX* are rewarded with higher fees. As investors learn about funds' stronger upside potential, they are indeed willing to pay higher fees and invest more in high-*MAX* funds with the expectation of receiving large positive returns in the future. Most importantly, these results suggest that the strong performance–flow relation found in hedge funds may be the evidence of a well-informed investor base for the hedge fund universe. Thus, upside potential, proxied by *MAX*, can be effectively used as an alternative complementary measure to standard performance measures when selecting individual hedge funds for future superior performance.

6. Upside Potential and Future Fund Performance by Investment Style

Hedge funds have various trading strategies: Some willingly take direct market exposure and risk (directional strategies, such as managed futures, global macro, and emerging market funds), while some try to minimize market risk altogether (non-directional strategies, such as equity market-neutral, fixed-income arbitrage, and convertible arbitrage funds), and some try to diversify market risk by taking both long and short diversified positions (semi-directional strategies, such as funds of funds, long-short equity hedge, event-driven, and multi-strategy funds). Given these various trading strategies and styles, one would expect to see varying degrees of upside potential and predictive ability for different hedge fund investment styles.

In this section, after classifying hedge funds into three broad investment strategies (directional, semi-directional, and non-directional), we first examine the link between *MAX* and funds' derivatives/leverage usage for each of the three broad investment strategies. We then test if the predictive power of *MAX* changes among individual investment styles. Second, we investigate the predictive power of *MAX* conditional on hedge funds' utilization of derivatives and leverage. Third, we investigate whether hedge funds can time fluctuations in the equity market and macroeconomic fundamentals. Lastly, we investigate the predictive power of *MAX* conditional on timing ability of hedge funds.

6.1. Predictive power of MAX by hedge fund investment style

Panel A of Table 10 provides information and statistics on directional, semi-directional, and non-directional hedge fund categories. The first row presents the number of funds in each of the three broad investment categories. The second row reports for the same three broad categories the percentages of hedge funds in the total sample. As shown in Table 10, Panel A, we have a total of 7,645 hedge funds in our TASS database that claim a specific investment strategy, 9.4% of which follow non-directional strategies, 20.2% of which follow directional strategies, with the remaining 70.4% following semi-directional strategies.

To understand the variation in upside potential among different investment strategies, we first analyze average *MAX*, the standard deviation of *MAX*, and the spread between the maximum and minimum values of *MAX* for these aforementioned three broad categories of hedge fund investment strategies. The third row in Table 10, Panel A, presents the cross-sectional average of individual funds' *MAX* within each category during the full sample period. The fourth row presents the cross-sectional average of the individual funds' time-series standard deviation of *MAX* within each category during the same sample period. The fifth row reports the cross-sectional average of the spread between the maximum and minimum values of *MAX* within each category. As noted by reading from left to right in Panel A of Table 10, the directional funds have noticeably larger *MAX* values, higher standard deviations of *MAX*, and greater max–min spreads of *MAX* compared to non-directional and semi-directional funds. In addition, the non-directional strategies' *MAX*, standard deviations of *MAX*, and max–min spreads of *MAX* are considerably smaller compared to those of the other strategies. Lastly, the semi-directional funds have average *MAX* values, standard deviations of *MAX*, and max–min spreads of *MAX* that are very similar to those of the entire hedge fund group.[20]

The last two rows in Panel A of Table 10 report, for each of the three broad investment categories separately, the percentages of funds that utilize futures and other derivatives in their investment strategies. Table 10, Panel A, clearly shows that the percentage of funds using futures and other derivatives increases monotonically as we move from the non-directional to the directional strategy group. Specifically, the percentage of funds using futures is 13.9% for the non-directional funds, 14% for the semi-directional funds, and 41% for the directional funds. Similarly, the percentage of funds using other derivatives is 17.5% for the non-directional funds, 18.5% for the semi-directional funds, and 24.1% for the directional funds. Overall, these results indicate that the directional funds employ a wide variety of dynamic trading strategies and make extensive use of derivatives, short selling, and leverage, causing their *MAX* values to be bigger and more volatile compared to the semi-directional and non-directional funds.

Based on this new set of results for various magnitudes of *MAX* and various degrees of derivatives usage among hedge fund investment strategies, we now investigate the predictive power of *MAX* for each individual hedge fund investment style separately. In Panel B of Table 10, we present the next-month average return and alpha spreads between the high-*MAX* and low-*MAX* quintiles for each style separately. Consistent with our earlier findings on derivatives usage, the predictive power of *MAX* is strongest for global macro, managed futures, and emerging market funds; for these directional funds, the average return (nine-factor alpha) spreads are very high in the range of 0.74% and 0.98% per month (0.58% and 0.71%) and highly significant with *t*-statistics ranging from 2.41 to 4.42 (2.26 to 3.77). On the other hand, interestingly, the predictive power of *MAX* is much lower for equity market-neutral, fixed-income arbitrage, and convertible arbitrage funds. For these non-directional funds, the average return (nine-factor alpha) spreads are much smaller in the range of 0.42% and 0.64% per month (0.25% and 0.41%) and statistically weaker, with *t*-statistics ranging from 1.63 to 3.09 (1.16 to 2.20). In fact, for convertible arbitrage funds, both the next month return and alpha spreads are statistically insignificant. Finally, the predictive power of *MAX* is also found to be economically and statistically significant for long-short equity hedge, multi-strategy, and event-driven funds. For these semi-directional funds, the average return (nine-factor alpha) spreads are in the range of 0.60% and 0.75% per month (0.45% and 0.48%) and significant

[20] Although not reported in Table 10, Panel A, we find that the average *MAX* of directional funds is significantly higher than the average *MAX* of non-directional and semi-directional funds and of all hedge funds in our sample.

with t-statistics ranging from 2.46 to 4.39 (2.16 to 3.60).[21] As can be noticed, the magnitude of return and alpha spreads for semi-directional funds are lower than those of directional funds, but larger than those of non-directional funds. In sum, we conclude that the predictive power of *MAX* gets stronger as we move from the least directional funds to the most directional funds in line with those funds' derivatives usage.

6.2. Predictive power of MAX by hedge funds with high vs. low derivatives/leverage use

In this section, we test the link between the predictive power of *MAX* and hedge funds' utilization of derivatives and leverage by performing a univariate portfolio test of *MAX* for funds using high leverage and derivatives vs. funds using low leverage and derivatives. Specifically, we rank our sample of 8,010 individual hedge funds based on their leverage and derivatives usage to generate two subsamples: a subsample of 400 hedge funds (approximately 5% of the total sample) to detect the funds with low leverage and no derivatives usage; and another subsample of 400 hedge funds to discover the funds with high leverage and derivatives usage.[22]

Panel A of Table 11 shows that, for funds with minimum leverage and no derivatives usage, the average return and alpha spreads between quintiles 5 and 1 are positive but economically and statistically insignificant, at 0.27% per month (t-stat. = 1.43) and 0.26% per month (t-stat. = 1.14), respectively, suggesting no evidence of a significant link between *MAX* and future returns for these static long-only hedge funds. On the contrary, Panel B of Table 11 shows that, for funds with the highest leverage and derivatives usage, the average return and alpha spreads between quintiles 5 and 1 are highly positive and economically and statistically significant, at 0.85% per month (t-stat. = 4.76) and 0.74% per month (t-stat. = 3.68), respectively, suggesting strong evidence of a significant link between *MAX* and future returns for these funds implementing dynamic trading strategies. These two substantial differences in results for these two sub-samples show evidence of a significant link between the predictive power of *MAX* and funds' utilization of leverage and derivatives. In sum, we conclude that this result is consistent with our conjecture that upside potential, driven by the dynamic trading strategies that use derivatives and leverage, is indeed an important determinant of the cross-sectional differences in hedge fund returns.

6.3. Market- and macro-timing ability of hedge funds

Our results until now show that there exists an economically and statistically stronger relation between upside potential and future returns for funds with higher *MAX* and more frequent usage of derivatives and leverage. Another possible explanation for the stronger performance of funds with higher *MAX* could be the market- and macro-timing ability of hedge fund managers. In this section, we provide a formal test of the market- and macro-timing ability for the directional, semi-directional, and non-directional

[21] As we show in Section 6.3, *MAX*'s predictive power is related to the market-timing ability of hedge fund managers. Funds of funds, on the other hand, rely on individual hedge fund managers' fund-picking ability, which is a very different skill set than the market-timing ability. For this reason, as shown in Table 10, Panel B, the predictive power of *MAX* is not significant for funds of funds.

[22] In the TASS database, we have information on whether a fund uses derivatives or not (a dummy variable of 1 if the fund uses derivatives, and zero if not) and also an average leverage magnitude for each hedge fund during their existence.

hedge funds. Specifically, we rely on the market-timing test of Henriksson and Merton (1981) and the macro-timing test of Bali, Brown, and Caglayan (2014). We implement the same methodology for each of the three broad categories of hedge fund styles separately and determine whether the ability to time market and macroeconomic changes is specific to a group of hedge funds.

We investigate the market-timing ability of hedge funds using pooled panel regressions based on the Henriksson–Merton model:

$$R_{i,t} = \alpha + \beta_1 \cdot MKT_t + \beta_2 \cdot MKT_t^{high} + \varepsilon_{i,t}, \tag{4}$$

where $R_{i,t}$ is the excess return of fund *i* in month *t*, MKT_t is the excess market return in month *t*, and MKT_t^{high} is the excess market return implying market-timing ability:

$$MKT_t^{high} = \begin{Bmatrix} MKT_t & \text{if } \; MKT_t \text{ is higher than its time-series median} \\ 0 & \text{otherwise} \end{Bmatrix}.$$

In Eq. (4), the regression parameters α, β_1, and β_2 are the intercept, market beta, and parameter for market-timing ability, respectively. Market timing indicates an increase (decrease) in market exposure prior to a market rise (fall), which results in a convex relation between fund returns and market returns. In this regression specification, a positive and significant estimate of β_2 implies the superior market-timing ability of individual hedge funds.

Following Bali, Brown, and Caglayan (2014), we also investigate the macro-timing ability of hedge funds using pooled panel regressions based on a modified model of Henriksson and Merton (1981). Specifically, MKT_t in Eq. (4) is replaced with the economic uncertainty index (UNC_t) of Bali et al. (2014).

Table 12 presents the estimated values of β_2 and the corresponding *t*-statistics from the pooled panel regression specification in Eq. (4) for the sample period January 1995 to December 2014. Pooled panel regressions are estimated separately for each of the three hedge fund categories (non-directional, semi-directional, and directional). The *t*-statistics reported in parentheses are estimated using clustered robust standard errors, accounting for two dimensions of cluster correlation (fund and year). This approach allows for correlations among different funds in the same year, as well as correlations among different years in the same fund (see Petersen (2009) for an estimation of clustered robust standard errors).

As reported in the first row of Table 12, for market-timing tests, β_2 is estimated to be positive, at 0.277, and highly significant, with a *t*-statistic of 2.62 for the directional hedge funds. The coefficient β_2 is also positive, 0.169, and significant, with a *t*-statistic of 2.07 for the semi-directional hedge funds. However, the statistical and economic significance of β_2 is higher for the directional funds than for the semi-directional funds. This indicates that directional hedge fund managers have a greater capability to time fluctuations in the equity market. On the other hand, consistent with our expectation, Table 12 shows that β_2 is economically and statistically insignificant for the non-directional funds, providing no evidence of market-timing ability for the non-directional hedge fund managers.

Similar results are obtained from the macro-timing tests. As presented in the last row of Table 12, β_2 is estimated to be positive, at 0.894, and highly significant, with a *t*-statistic of 2.58 for the directional hedge funds. Similar to our earlier findings from the market-timing tests, β_2 is also positive, at 0.494, and significant, with a *t*-statistic of 2.32 for the semi-directional hedge funds. Consistent with the findings of Bali, Brown, and Caglayan (2014), the statistical and economic significance of β_2 is higher for the directional funds than for the semi-directional funds, implying that directional hedge fund managers have a higher capability to time fluctuations in macroeconomic changes. As expected, β_2 is again economically and statistically insignificant for the non-directional funds, providing no evidence of macro-timing ability for the non-directional hedge fund managers.

Overall, these results make sense in the real-world setting of hedge funds, since directional funds willingly take direct exposure to financial and macroeconomic risk factors, relying on their market- and macro-timing abilities to generate superior returns. Since these are funds with dynamic trading strategies frequently using derivatives/leverage that are highly exposed to market and macroeconomic risk, timing the switch in economic trends is essential to their success. Hence, our previous results, which show a stronger link between *MAX* and future returns for the directional funds can be attributed to the evidence of the superior market- and macro-timing abilities of these directional hedge fund managers.

6.4. Predictive power of MAX conditional on the timing ability of hedge funds

In the previous section, we check whether market-timing ability is specific to a group of hedge funds via pooled panel regressions based on Henriksson–Merton model and find that the market-timing ability coefficient (β_2) from Regression Eq. (4) is strongest for directional funds. We also document earlier that the predictive power of *MAX* is strongest for directional funds in our portfolio tests. To directly test the link between the predictive power of *MAX* and funds' market-timing ability at the fund level, we now perform a univariate portfolio test of *MAX* for funds with high market-timing ability vs. funds with low market-timing ability. Specifically, we run Eq. (4) for each fund separately for the full-sample period and rank our sample of 8,010 individual hedge funds based on their market-timing ability coefficient (β_2) to generate two subsamples: a subsample of 400 hedge funds (approximately 5% of the total sample) to detect the funds with no market-timing ability; and another subsample of 400 hedge funds to discover the funds with the best market-timing ability.

Table 13 reports results from univariate portfolios of funds sorted by *MAX* conditional on low and high market-timing ability of funds measured by the magnitutes of the market-timing coefficients from Eq. (4). In Panel A of Table 13, we see that for funds with low or no market-timing ability, the average return and alpha spreads between quintiles 5 and 1 are positive but economically and statistically insignificant, at 0.30% per month (*t*-stat. = 1.56) and 0.21% per month (*t*-stat. = 0.86), respectively, suggesting no evidence of a significant link between *MAX* and future returns for this group of funds with no market-timing ability. In contrast, Panel B of Table 13 shows that, for funds with strong market-timing ability, the average return and alpha spreads between quintiles 5 and 1 are highly positive and economically and statistically significant, at both 0.91% per month (*t*-statistics 2.55 and 2.11), respectively, suggesting strong evidence of a significant link between *MAX* and future returns for these funds with high market-timing ability. In sum, these sharp differences in results for these two sub-samples provide evidence of a significant link between the predictive power of *MAX* and funds' market-timing ability, suggesting that *MAX* through market-timing ability has a strong predictive power over the cross-sectional differences in future hedge fund returns.[23]

7. Conclusion

This paper shows that the significant concentration of the financial press and the investors on extraordinarily successful funds with very high past returns and the return chasing behavior of hedge fund investors may not be irrational after all. We propose a measure of upside potential based on the maximum monthly returns of hedge funds (*MAX*) over as low as just 12 months of data, and show that *MAX* has a strong predictive power over future hedge fund returns, while capturing the option-like features of hedge fund payoffs at the same time. Importantly, *MAX* also contains persistent, significant information about future upside potential that is orthogonal to the standard measures of performance as it has low correlation with alpha, appraisal ratio, and Sharpe ratio.

Hedge funds in the highest *MAX* quintile (with strong upside potential) generate 70 basis points per month higher returns than funds in the lowest *MAX* quintile (with weak upside potential). After controlling for the four Fama-French-Carhart factors of market, size, book-to-market, and momentum, as well as Fung and Hsieh's five trend-following factors on currencies, bonds, commodities, short-term interest rates, and stock indexes, we find that the nine-factor alpha spread between the high-*MAX* and low-*MAX* funds remains positive, 0.47% per month, and highly significant. We also run fund-level cross-sectional regressions to control for fund characteristics as well as alternative risk and performance measures simultaneously. Both Fama-MacBeth regressions and portfolio-level analyses provide strong corroborating evidence of an economically and statistically significant positive relation between *MAX* (upside potential) and future hedge fund returns. More importantly, we demonstrate that funds with strong upside potential attract more capital, charge higher fees, and have higher probability of survival. Moreover, in our tests for the long-term predictive power of *MAX*, we provide evidence that the positive relation between *MAX* and future fund returns is not just a one-month affair. The predictive power of *MAX* remains strong for more than one year into the future. That is, funds with a higher *MAX* outperform funds with a lower *MAX*, not just for one month, but for as long as 1.5 years into the future in risk-adjusted terms.

Once we establish our main finding that upside potential (*MAX*) is a strong determinat of future hedge fund returns, we test if the predictive power of *MAX* gradually increases as we move from the least

[23] Section VIII of the Online Appendix provides an alternative explanation for the superior (inferior) performance of the directional (non-directional) hedge funds by replicating our main analyses for the mutual fund industry. Since mutual funds do not use dynamic trading strategies and tend to invest primarily on the long side without extensively using other tools (e.g., derivatives, leverage, and short-selling), Table XIII of the Online Appendix provides no evidence for a significant link between *MAX* and future mutual fund returns. Table XIII also shows that mutual funds, as in the case of the non-directional hedge funds, do not have significant market- or macro-timing ability.

directional strategies to the most directional strategies. Consistent with our expectations, the predictive power of *MAX* turns out to be the highest for the directional funds. These directional funds, with higher *MAX*, are also the funds that employ a wide variety of dynamic trading strategies and make extensive use of derivatives and leverage. In contrast, the predictive power of *MAX* is found to be the lowest for non-directional funds, with a lower *MAX*, and with lower usage of derivatives and leverage.

We also investigate whether hedge funds have the ability to time fluctuations in the equity market and macroeconomic fundamentals. The results indicate that directional hedge fund managers can predict and exploit changes in market and macroeconomic conditions by increasing (decreasing) fund exposure to risk factors when market risk and/or economic uncertainty is high (low). However, for hedge funds with no market-timing ability, there seems to be no link between *MAX* and future returns. This suggests that *MAX*, through derivatives and leverage usage, and funds' market-timing ability, has a strong predictive power on the cross-sectional differences in future hedge fund returns. Overall, our findings suggest that *MAX* is a robust measure of upside potential that complements standard performance measures, which can also be effectively used by investors when selecting individual hedge funds for superior performance in the future.

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Table 1. Univariate Portfolios of Hedge Funds Sorted by *MAX*

Panel A. Univariate Portfolios of Alternative *MAX* measures

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their alternative *MAX* measures. *MAX6*, *MAX9*, *MAX12*, *MAX18*, and *MAX24* represent the maximum monthly hedge fund returns over the last 6, 9, 12, 18, and 24 months, respectively. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* measures, and quintile 5 is the portfolio of hedge funds with the highest *MAX* measures. In each column, the top panel reports the average *MAX* measures in each quintile, and the lower panel reports those same quintiles' next month average returns. The last two rows show the monthly average raw return differences and the 9-factor Alpha differences between quintile 5 (High *MAX* funds) and quintile 1 (low *MAX* funds). Average returns and Alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

	Average Size of *MAX6*	Average Size of *MAX9*	Average Size of *MAX12*	Average Size of *MAX18*	Average Size of *MAX24*
Q1	1.07	1.45	1.67	1.98	2.20
Q2	2.20	2.69	3.04	3.57	3.96
Q3	3.46	4.17	4.69	5.46	6.04
Q4	5.58	6.61	7.39	8.54	9.41
Q5	12.67	14.51	15.88	17.94	19.52
	Next-month returns of *MAX6* Quintiles	Next-month returns of *MAX9* Quintiles	Next-month returns of *MAX12* Quintiles	Next-month returns of *MAX18* Quintiles	Next-month returns of *MAX24* Quintiles
Q1	0.10	0.08	0.09	0.11	0.14
Q2	0.30	0.33	0.33	0.33	0.30
Q3	0.43	0.44	0.45	0.43	0.38
Q4	0.59	0.60	0.58	0.55	0.51
Q5	0.91	0.83	0.79	0.67	0.64
Q5 – Q1 Return Diff.	**0.81** **(3.85)**	**0.75** **(3.79)**	**0.70** **(3.48)**	**0.56** **(3.01)**	**0.51** **(2.71)**
Q5 – Q1 9-factor Alpha Diff.	**0.55** **(2.87)**	**0.50** **(2.70)**	**0.47** **(2.44)**	**0.39** **(2.10)**	**0.36** **(2.04)**

Table 1 (continued)

Panel B. Average Raw and Risk-Adjusted Returns of *MAX* Quintile Portfolios

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *MAX*. Quintile 1 is the portfolio of hedge funds with the lowest *MAX*, and quintile 5 is the portfolio of hedge funds with the highest *MAX*. The table reports average *MAX* in each quintile, the next month average returns, and the 9-factor alphas for each quintile. The last row shows the average monthly raw return difference and the 9-factor alpha difference between High *MAX* and Low *MAX* quintiles. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the returns and alphas.

Quintiles	Average *MAX* in each Quintile	Next Month Average Returns	Next Month 9-Factor Alphas
Q1	1.67	0.09	–0.01
		(1.08)	(–0.20)
Q2	3.04	**0.33**	**0.20**
		(3.20)	**(2.56)**
Q3	4.69	**0.45**	**0.29**
		(3.63)	**(3.54)**
Q4	7.39	**0.58**	**0.32**
		(3.61)	**(3.00)**
Q5	15.88	**0.79**	**0.46**
		(3.13)	**(2.25)**
Q5 – Q1		**0.70**	**0.47**
t-statistic		**(3.48)**	**(2.44)**

Table 2. Persistence of *MAX*

Panel A. 12-month-ahead Transition Matrix

This table reports the average month-to-month portfolio transition matrix in 12 months ahead. The table presents the average probability that a fund in quintile *i* (defined by the rows) in one month will be in quintile *j* (defined by the columns) in the subsequent 12 months. If *MAX* is completely random, then all the probabilities should be approximately 20%, since a *high-MAX* or *low-MAX* in one month should say nothing about the *MAX* in the following 12 months. Instead, all diagonal elements from top left to bottom right of the transition matrix exceed 20%, illustrating that the maximum return over the past 12 months is highly persistent even after putting a 12-month gap between the lagged and lead *MAX* variables. The sample period is January 1995–December 2014.

	Low *MAX*	Q2	Q3	Q4	High *MAX*	Total
Low *MAX*	59.5%	24.9%	10.0%	3.8%	1.8%	100.0%
Q2	25.8%	35.7%	23.7%	10.8%	4.0%	100.0%
Q3	10.0%	24.5%	32.5%	23.1%	10.0%	100.0%
Q4	4.4%	10.7%	23.5%	35.6%	25.8%	100.0%
High *MAX*	1.6%	4.1%	10.0%	26.1%	58.2%	100.0%

Table 2 (continued)

Panel B. Fama-MacBeth Cross-sectional Regressions of 12-month-ahead *MAX* on Current *MAX* and Control Variables

This table reports the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of 12-month-ahead *MAX* on current *MAX*, *MIN*, the past 24-month 9-factor alpha (*Alpha*), the past 12-month average return (*AVRG*), the past 12-month standard deviation (*STDEV*), the past one-month return (*LagRet*), and fund characteristics. Monthly Fama-MacBeth regressions are run for the period January 1995–December 2014. Newey-West *t*-statistics are reported in parentheses. Numbers in bold denote statistical significance.

Intercept	*MAX*	*MIN*	Alpha	AVRG	STDEV	LagRet	Size	Age	Flow	IncentFee	MgtFee	MinInv	Redemption	DLockup	DLever	R^2
2.381	**0.530**															**28.47%**
(14.35)	**(30.35)**															**(27.63)**
2.666		**0.394**														**22.36%**
(14.09)		**(19.53)**														**(18.11)**
5.266			**0.490**													**5.43%**
(18.28)			**(3.46)**													**(6.92)**
5.105				**0.482**												**5.58%**
(17.30)				**(4.16)**												**(6.70)**
5.786					**1.150**											**6.66%**
(21.32)					**(18.86)**											**(11.11)**
5.386						**0.076**										**4.60%**
(19.94)						**(3.29)**										**(10.74)**
5.847							**–0.425**									**0.25%**
(21.75)							**(–3.62)**									**(9.69)**
6.431								–0.048								**0.16%**
(9.36)								(–1.11)								**(5.55)**
5.786									0.001							**0.11%**
(21.33)									(0.34)							**(5.02)**
3.829										**0.130**						**3.16%**
(15.24)										**(22.53)**						**(16.46)**
4.953											**0.573**					**0.80%**
(15.88)											**(10.55)**					**(7.29)**
5.849												**–0.065**				**0.19%**
(21.18)												**(–9.39)**				**(15.02)**
6.466													**–0.020**			**1.22%**
(23.70)													**(–11.35)**			**(8.69)**
5.686														**0.408**		**0.22%**
(21.18)														**(4.14)**		**(5.63)**
5.152															**1.092**	**0.91%**
(20.32)															**(15.98)**	**(9.76)**
0.660	**0.428**	**0.071**	**0.411**	–0.032	**1.053**	**0.026**	–0.069	0.017	**0.006**	**0.035**	0.027	**–0.009**	0.002	**0.265**	**0.177**	**40.63%**
(1.03)	**(18.59)**	**(3.15)**	**(6.68)**	(–0.37)	**(10.40)**	**(2.20)**	(–1.42)	(1.11)	**(2.86)**	**(6.24)**	(0.65)	**(–2.88)**	(1.17)	**(3.82)**	**(5.12)**	**(34.74)**

Table 3. Conditional Bivariate Portfolios of *MAX* Controlling for AVRG, STDEV, Sharpe Ratio, Alpha, Appraisal Ratio, Incentive Fee, and Fund Flows

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds first based on their fund characteristics (AVRG, STDEV, Sharpe Ratio, 9-factor Alpha, 9-factor Appraisal Ratio, Incentive Fee, and Fund Flows) separately. Then, within each fund characteristics sorted portfolio, hedge funds are further sorted into sub-quintiles based on their *MAX*. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* within each fund characteristics sorted quintile portfolio (depending on which fund characteristic's effect on *MAX* is controlled for) and Quintile 5 is the portfolio of hedge funds with the highest *MAX* within each fund characteristics sorted quintile portfolio (again depending on which fund characteristic's effect on *MAX* is controlled for). In each column, the top panel reports the average *MAX* in each quintile, and the lower panel reports those same quintiles' next month average returns. The last two rows show the monthly average raw return differences and the 9-factor Alpha differences between quintile 5 (High-*MAX* funds) and quintile 1 (low-*MAX* funds). Average returns and Alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

	MAX portfolios controlling for AVRG	*MAX* portfolios controlling for STDEV	*MAX* portfolios controlling for SR	*MAX* portfolios controlling for 9-factor Alpha	*MAX* portfolios controlling for 9-factor AR	*MAX* portfolios controlling for Incentive Fee	*MAX* portfolios controlling for Fund Flows
Q1	2.39	3.42	1.84	2.05	1.78	1.76	1.75
Q2	3.74	4.96	3.24	3.48	3.13	3.26	3.15
Q3	5.16	6.04	4.85	5.00	4.71	4.90	4.78
Q4	7.30	7.38	7.42	7.34	7.32	7.38	7.38
Q5	14.06	10.86	15.30	14.57	15.47	15.36	15.60
	Next-month returns of *MAX* Quintiles	Next-month returns of *MAX* Quintiles	Next-month returns of *MAX* Quintiles	Next-month returns of *MAX* Quintiles	Next-month returns of *MAX* Quintiles	Next-month returns of *MAX* Quintiles	Next-month returns of *MAX* Quintiles
Q1	0.21	0.06	0.12	0.10	0.04	0.10	0.09
Q2	0.37	0.34	0.32	0.30	0.29	0.34	0.35
Q3	0.47	0.49	0.45	0.42	0.39	0.47	0.45
Q4	0.53	0.61	0.56	0.48	0.53	0.55	0.58
Q5	0.65	0.75	0.79	0.67	0.73	0.78	0.77
Q5 – Q1 Return Diff.	**0.44** **(3.02)**	**0.69** **(5.71)**	**0.67** **(3.39)**	**0.57** **(3.18)**	**0.69** **(3.46)**	**0.68** **(3.37)**	**0.68** **(3.55)**
Q5 – Q1 9-factor Alpha Diff.	**0.29** **(2.09)**	**0.68** **(5.00)**	**0.41** **(2.40)**	**0.39** **(2.30)**	**0.50** **(2.60)**	**0.46** **(2.44)**	**0.45** **(2.47)**

Table 4. Independent Bivariate Sorts of *MAX* and Alpha

This table conducts an independently sorted bivariate portfolio analysis of *MAX* and the 9-factor alpha. For each month from January 1996 to December 2014, we rank hedge funds according to their *MAX* and the 9-Factor alpha independently at the same time and assign a quintile number (from 1 to 5, 1 being lowest category and 5 being highest category) to each hedge fund (for each *MAX* and Alpha category) based on its rankings. This generates 25 sub-quintiles of hedge funds, where each hedge fund is put in one of these 25 sub-quintiles depending on the hedge fund's rank within its peers with respect to its *MAX* and Alpha measure. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* (Alpha) within each Alpha (*MAX*) sorted quintile portfolio and Quintile 5 is the portfolio of hedge funds with the highest *MAX* (Alpha) within each Alpha (*MAX*) sorted quintile portfolio. The row "Average" presents the next-month returns of *MAX* quintile portfolios averaged across the Alpha quintiles. The column "Average" presents the next-month returns of Alpha quintile portfolios averaged across the *MAX* quintiles. The last two columns show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*MAX* funds) and quintile 1 (Low-*MAX* funds) within each Alpha quintile. The last two rows show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-Alpha funds) and quintile 1 (Low-Alpha funds) within each *MAX* quintile. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

		MAX quintiles							
		Q1	Q2	Q3	Q4	Q5	Average	Q5–Q1 Ret Diff.	Q5–Q1 Alpha Diff.
Alpha quintiles	Q1	-0.48	-0.03	0.19	0.23	0.52	0.09	**1.00 (4.40)**	**0.80 (3.23)**
	Q2	-0.07	0.21	0.32	0.48	0.51	0.29	**0.57 (2.76)**	**0.48 (2.33)**
	Q3	0.10	0.33	0.42	0.51	0.70	0.41	**0.60 (2.80)**	**0.50 (2.18)**
	Q4	0.17	0.42	0.46	0.60	0.80	0.49	**0.63 (3.12)**	**0.44 (2.08)**
	Q5	0.29	0.52	0.64	0.75	0.94	0.63	**0.66 (2.70)**	**0.50 (2.01)**
	Average	0.01	0.29	0.41	0.51	0.69		**0.69 (3.69)**	**0.54 (2.79)**
	Q5–Q1 Ret Diff.	**0.77**	**0.55**	**0.45**	**0.52**	**0.42**	**0.54**		
		(6.42)	**(6.51)**	**(5.99)**	**(3.64)**	**(2.51)**	**(6.35)**		
	Q5–Q1 Alpha Diff.	**0.79**	**0.63**	**0.50**	**0.70**	**0.50**	**0.62**		
		(5.64)	**(8.18)**	**(5.02)**	**(4.04)**	**(2.84)**	**(8.47)**		

Table 5. Independent Bivariate Sorts of *MAX* and *MIN*

This table conducts an independently sorted bivariate portfolio analysis of *MAX* and *MIN*. For each month from January 1995 to December 2014, we rank hedge funds according to their *MAX* and *MIN* independently at the same time and assign a quintile number (from 1 to 5, 1 being lowest category and 5 being highest category) to each hedge fund (for each *MAX* and *MIN* category) based on its rankings. This generates 25 sub-quintiles of hedge funds, where each hedge fund is put in one of these 25 sub-quintiles depending on the hedge fund's rank within its peers with respect to its *MAX* and *MIN* measure. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* (*MIN*) within each *MIN* (*MAX*) sorted quintile portfolio and Quintile 5 is the portfolio of hedge funds with the highest *MAX* (*MIN*) within each *MIN* (*MAX*) sorted quintile portfolio. The row "Average" presents the next-month returns of *MAX* quintile portfolios averaged across the *MIN* quintiles. The column "Average" presents the next-month returns of *MIN* quintile portfolios averaged across the *MAX* quintiles. The last two columns show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*MAX* funds) and quintile 1 (Low-*MAX* funds) within each *MIN* quintile. The last two rows show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*MIN* funds) and quintile 1 (Low-*MIN* funds) within each *MAX* quintile. Average returns and alphas are defined in monthly percentage terms. Newey-West *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

		MAX quintiles							
		Q1	Q2	Q3	Q4	Q5	Average	Q5–Q1 Ret Diff.	Q5–Q1 Alpha Diff.
	Q1	0.19	0.42	0.54	0.70	0.91	0.55	**0.72 (3.81)**	**0.80 (3.98)**
	Q2	0.11	0.36	0.43	0.57	0.58	0.41	**0.47 (3.18)**	**0.61 (4.03)**
MIN quintiles	Q3	-0.03	0.26	0.49	0.50	0.62	0.37	**0.65 (3.36)**	**0.58 (2.67)**
	Q4	-0.09	0.21	0.41	0.61	0.68	0.36	**0.77 (4.04)**	**0.59 (2.82)**
	Q5	-0.86	-0.06	0.30	0.43	0.74	0.11	**1.61 (5.75)**	**1.28 (4.74)**
	Average	-0.14	0.24	0.43	0.56	0.71		**0.85 (6.12)**	**0.77 (5.16)**
	Q5–Q1 Ret Diff.	**-1.05**	**-0.48**	-0.24	-0.27	-0.16	-0.44		
		(-3.25)	**(-2.05)**	(-1.50)	(-1.18)	(-0.50)	(-1.56)		
	Q5–Q1 Alpha Diff.	**-0.75**	**-0.33**	-0.18	-0.31	-0.14	-0.23		
		(-2.32)	**(-1.85)**	(-1.27)	(-0.84)	(-0.48)	(-1.43)		

Table 6. Fama-MacBeth Cross-sectional Regressions with *MAX* and Control Variables

This table reports the average intercept and average slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month-ahead hedge fund excess returns on *MAX* with and without control variables. The Fama-MacBeth regressions are run each month for the period January 1995–December 2014. The multivariate regressions in columns (2) through (4) are run controlling for three alternative performance measures (Sharpe Ratio (SR), 9-Factor Alpha, and 9-Factor Appraisal Ratio (AR)) separately one at a time. Newey-West *t*-statistics are reported in parentheses. Numbers in bold denote statistical significance of the average slope coefficients.

	(1)	(2)	(3)	(4)
Intercept	0.208 (2.25)	0.053 (0.22)	–0.077 (–0.46)	–0.025 (–0.13)
MAX	**0.042** **(3.52)**	**0.037** **(2.78)**	**0.036** **(3.12)**	**0.036** **(2.96)**
MIN		–0.010 (–1.20)	–0.007 (–1.00)	–0.007 (–0.99)
Sharpe Ratio (SR)		**0.123** **(2.58)**		
SR × *MAX*		**0.050** **(2.19)**		
Alpha			**0.134** **(3.16)**	
Alpha × *MAX*			**0.009** **(2.10)**	
Appraisal Ratio (AR)				**0.137** **(4.79)**
AR × *MAX*				**0.026** **(2.14)**
AVRG		**0.209** **(3.10)**	**0.194** **(3.94)**	**0.208** **(4.30)**
STDEV		**0.097** **(1.97)**	**0.090** **(2.11)**	**0.092** **(2.10)**
Lagret		**0.060** **(4.32)**	**0.060** **(4.31)**	**0.058** **(4.19)**
Size		0.001 (0.04)	–0.002 (–0.07)	–0.003 (–0.09)
Age		–0.002 (–0.36)	0.001 (0.43)	–0.001 (–0.07)
Flow		–0.001 (–0.73)	–0.001 (–0.93)	–0.001 (–0.81)
IncentFee		**0.004** **(2.22)**	**0.004** **(2.14)**	**0.004** **(2.27)**
MgmtFee		0.016 (0.49)	0.012 (0.35)	0.013 (0.39)
MinInv		**0.004** **(3.21)**	**0.004** **(3.30)**	**0.004** **(3.31)**
Redemption		**0.001** **(1.92)**	**0.002** **(2.16)**	**0.002** **(1.96)**
DLockup		**0.071** **(2.18)**	**0.074** **(2.28)**	**0.077** **(2.33)**
Dlever		0.024 (1.13)	0.027 (1.25)	0.026 (1.23)

Table 7. Long-term Predictive Power of *MAX*

This table investigates the long-term predictive power of *MAX*. In Panel A, quintile portfolios are formed each quarter by sorting hedge funds based on their *MAX* measures. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* and quintile 5 is the portfolio of hedge funds with the highest *MAX*. Panel A reports the 1-quarter to 8-quarter ahead average quarterly returns for each of the five quintiles. The last two rows in Panel A show the average return differences and the 9-factor alpha differences between quintile 5 (*high-MAX* funds) and quintile 1 (*low-MAX* funds). Panel B presents the average intercept and average slope coefficients from the Fama-MacBeth cross-sectional regressions of 3-month-ahead and 12-month-ahead hedge fund excess returns on *MAX* with and without control variables. The Fama-MacBeth regressions are run each month for the period January 1995–December 2014. Newey-West *t*-statistics are reported in parentheses. Numbers in bold denote statistical significance of the average slope coefficients.

Panel A. Univariate Portfolio Results

	1-quarter ahead Average Return	2-quarter ahead Average Return	3-quarter ahead Average Return	4-quarter ahead Average Return	5-quarter ahead Average Return	6-quarter ahead Average Return	7-quarter ahead Average Return	8-quarter ahead Average Return
Q1	0.42	0.52	0.57	0.56	0.56	0.57	0.59	0.60
Q2	1.04	1.12	1.02	1.02	0.93	0.85	0.82	0.83
Q3	1.42	1.46	1.35	1.19	1.18	1.09	1.02	1.03
Q4	1.77	1.62	1.54	1.44	1.35	1.28	1.16	1.16
Q5	2.48	2.02	1.88	1.75	1.64	1.70	1.57	1.44
Q5 – Q1 Return Diff.	**2.05** **(3.39)**	**1.51** **(2.87)**	**1.32** **(2.82)**	**1.20** **(2.58)**	**1.09** **(2.50)**	**1.13** **(2.80)**	**0.99** **(2.37)**	**0.84** **(2.01)**
Q5 – Q1 9-factor Alpha Diff.	**1.81** **(2.49)**	**1.25** **(2.15)**	**1.15** **(2.15)**	**1.10** **(2.13)**	**1.01** **(2.08)**	**0.92** **(1.98)**	0.72 (1.54)	0.51 (1.10)

Table 7 (continued)

Panel B. Fama-MacBeth Cross-Sectional Regressions

	3-Month-ahead Predictability of *MAX*		12-Month-ahead Predictability of *MAX*	
	(1)	(2)	(1)	(2)
Intercept	0.209 (2.01)	0.187 (0.60)	0.262 (2.50)	–0.617 (–0.86)
MAX	**0.034** **(2.93)**	**0.033** **(2.45)**	**0.026** **(2.85)**	**0.033** **(2.57)**
MIN		–0.005 (–0.62)		–0.012 (–1.23)
Sharpe Ratio (SR)		**0.137** **(2.77)**		**0.092** **(2.12)**
SR × *MAX*		**0.067** **(2.10)**		**0.067** **(2.49)**
AVRG		**0.209** **(3.17)**		0.038 (0.55)
STDEV		0.042 (0.83)		0.075 (1.60)
Lagret		0.016 (1.08)		0.001 (0.07)
Size		–0.002 (–0.05)		–0.029 (–0.90)
Age		–0.007 (–0.91)		0.019 (1.00)
Flow		–0.001 (–0.87)		–0.001 (–0.53)
IncentFee		0.003 (1.32)		**0.004** **(1.87)**
MgmtFee		0.022 (0.65)		0.005 (0.15)
MinInv		**0.005** **(3.54)**		**0.006** **(4.06)**
Redemption		**0.002** **(2.37)**		**0.003** **(2.92)**
DLockup		**0.080** **(2.37)**		**0.079** **(2.03)**
Dlever		0.016 (0.73)		0.039 (1.66)

Table 8. Fama-MacBeth Cross-sectional Logit Regressions of Hedge Fund Survival on *MAX* and Control Variables

This table reports the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month-, three-month-, and twelve-month-ahead hedge fund survival (measured as a dummy variable taking the value of 1 if the fund is in existence, or 0 if the fund is deceased) on *MAX* with and without control variables using Logit regressions. The Logit cross-sectional regressions are run each month for the period January 2002–December 2014. Newey-West *t*-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. Numbers in bold denote statistical significance of the average slope coefficients.

	Panel A *1-month-ahead Fund Survival Regressed on MAX & Control Variables*		**Panel B** *3-month-ahead Fund Survival Regressed on MAX & Control Variables*		**Panel C** *12-month-ahead Fund Survival Regressed on MAX & Control Variables*	
	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	4.137 (39.76)	3.703 (24.39)	3.252 (31.75)	2.758 (23.66)	1.819 (18.34)	1.360 (15.04)
MAX	**0.034** **(5.94)**	**0.051** **(6.42)**	**0.013** **(2.83)**	**0.018** **(2.65)**	**0.012** **(2.94)**	**0.017** **(2.35)**
MIN		0.001 (0.20)		**–0.015** **(–2.92)**		**–0.021** **(–4.80)**
Sharpe Ratio (SR)		**0.595** **(7.21)**		**0.626** **(7.15)**		**0.589** **(7.05)**
SR × *MAX*		**0.094** **(2.10)**		**0.045** **(2.42)**		**0.100** **(7.23)**
AVRG		0.068 (0.80)		**0.269** **(6.95)**		**0.383** **(10.77)**
STDEV		**0.152** **(3.24)**		**0.103** **(3.98)**		**0.117** **(6.90)**
Lagret		**0.021** **(2.15)**		**0.018** **(4.71)**		**0.016** **(4.97)**
Size		**2.192** **(5.85)**		**1.144** **(4.19)**		**0.482** **(3.16)**
Age		**0.003** **(4.64)**		**0.003** **(4.69)**		**0.004** **(6.91)**
Flow		**0.014** **(6.29)**		**0.017** **(11.60)**		**0.017** **(12.19)**
IncentFee		**–0.014** **(–3.28)**		**–0.012** **(–3.26)**		**–0.013** **(–3.97)**
MgmtFee		**0.122** **(2.71)**		**0.124** **(2.93)**		**0.078** **(2.41)**
MinInv		**0.095** **(5.56)**		**0.053** **(3.94)**		**0.035** **(3.75)**
Redemption		**0.003** **(2.44)**		**0.003** **(2.44)**		**0.003** **(2.83)**
DLockup		**–0.135** **(–2.52)**		–0.060 (–1.00)		–0.047 (–0.86)
Dlever		–0.013 (–0.33)		0.015 (0.46)		0.023 (1.10)

Table 9. Fama-MacBeth Regressions of Hedge Fund Fees and One-month-ahead Hedge Fund Flows on *MAX* and Control Variables

This table reports the average intercept and average slope coefficients from the Fama-MacBeth cross-sectional regressions of Incentive Fees, Management Fees, and one-month-ahead Flows (separately) on *MAX* with and without control variables. The Fama-MacBeth regressions are run each month for the period January 1995–December 2014, and the average slope coefficients are calculated for the full sample period. Newey-West *t*-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. Numbers in bold denote statistical significance of the average slope coefficients.

Panel A: Cross-sectional regressions of Incentive Fee on MAX with and without control variables:

Intercept	*MAX*	*MIN*	SR	STDEV	LagRet	Size	Age	Flow	MgtFee	MinInv	Redemption	DLockup	DLever
13.378	**0.283**												
(142.48)	**(20.54)**												
10.492	**0.199**	**0.097**	**0.946**	**0.213**	–0.011	0.051	**–0.028**	0.005	**0.892**	**0.048**	–0.001	**3.273**	**3.591**
(19.17)	**(13.17)**	**(4.67)**	**(4.18)**	**(3.32)**	(–1.12)	(0.87)	**(–2.61)**	(1.38)	**(6.75)**	**(7.61)**	(–0.45)	**(31.88)**	**(74.40)**

Panel B: Cross-sectional regressions of Management Fee on MAX with and without control variables:

Intercept	*MAX*	*MIN*	SR	STDEV	LagRet	Size	Age	Flow	IncentFee	MinInv	Redemption	DLockup	DLever
1.383	**0.012**												
(214.92)	**(10.12)**												
1.321	**0.008**	**–0.002**	**–0.057**	**0.019**	–0.002	–0.007	**0.002**	**–0.001**	**0.007**	**–0.007**	**–0.003**	**–0.168**	**0.108**
(31.48)	**(6.48)**	**(–1.94)**	**(–3.54)**	**(3.21)**	(–1.48)	(–0.48)	**(1.77)**	**(–2.20)**	**(8.61)**	**(–16.29)**	**(–8.37)**	**(–20.53)**	**(13.61)**

Panel C: Cross-sectional regressions of one-month-ahead Hedge Fund Flows on MAX with and without control variables:

Intercept	*MAX*	*MIN*	SR	STDEV	LagRet	Size	Age	MgtFee	IncentFee	MinInv	Redemption	DLockup	DLever
–0.410	**0.020**												
(–3.75)	**(2.96)**												
0.466	**0.019**	0.010	**1.137**	**–0.194**	**0.017**	0.026	–0.040	–0.049	0.004	0.002	**0.002**	**0.135**	**0.123**
(0.43)	**(2.38)**	(1.62)	**(9.20)**	**(–5.11)**	**(2.38)**	(0.41)	(–1.38)	(–1.38)	(1.11)	(0.77)	**(2.43)**	**(2.84)**	**(2.62)**

Table 10. Investment Style Analyses of *MAX*

Panel A. *MAX* by Three Broad Hedge Fund Categories

The first and second rows of this table present the number of funds and the percentage of hedge funds in total sample for each of the three broad hedge fund investment style categories. The third, fourth, and fifth rows report, respectively, the cross-sectional average of individual funds' *MAX* within each category, the cross-sectional average of the individual funds' time-series standard deviation of *MAX*, and the cross-sectional average of the spread between Max and Min of *MAX* for each of the three investment styles separately. The sixth and seventh rows report, for each of the three broad investment categories separately, the percentages of funds that utilize futures and other derivatives in their investment strategies. For comparison purposes, the same statistics across all hedge funds (irrespective of the hedge fund categories) are also reported in the last column.

	Non-directional Hedge Funds	Semi-directional Hedge Funds	Directional Hedge Funds	All Hedge Funds
Number of Funds	718	5,383	1,544	7,645
% of Funds in total sample	9.4%	70.4%	20.2%	100.0%
Average *MAX*	4.05	5.98	9.61	6.56
Avg. Std. Dev. of *MAX*	1.76	2.43	3.75	2.63
Avg. Max–Min spread of *MAX*	5.61	7.95	12.25	8.60
% of Funds using Futures	13.9%	14.0%	41.0%	19.9%
% of Funds using other Derivatives	17.5%	18.5%	24.1%	19.6%

Table 10 (continued)

Panel B. Univariate Portfolios of Hedge Funds Sorted by *MAX* within Each Hedge Fund Investment Style

For each hedge fund investment style separately, univariate quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *MAX*. Quintile 1 is the portfolio of hedge funds with the lowest *MAX*, and quintile 5 is the portfolio of hedge funds with the highest *MAX* within each investment style. The table reports the average monthly raw return difference and the 9-factor alpha difference between High *MAX* and Low *MAX* quintiles. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

Hedge Fund Styles	Next Month Return Difference	9-Factor Alpha Difference
Convertible Arbitrage	0.42	0.25
	(1.63)	(1.16)
Equity Market Neutral	**0.59**	**0.38**
	(3.09)	**(2.20)**
Fixed Income Arbitrage	**0.64**	**0.41**
	(2.46)	**(2.11)**
Fund of Funds	**0.29**	0.17
	(1.79)	(1.07)
Long-short Equity Hedge	**0.60**	**0.45**
	(2.46)	**(2.16)**
Multi Strategy	**0.63**	**0.46**
	(4.39)	**(3.60)**
Event Driven	**0.75**	**0.48**
	(3.53)	**(3.00)**
Global Macro	**0.74**	**0.64**
	(3.61)	**(2.93)**
Managed Futures	**0.82**	**0.71**
	(4.42)	**(3.77)**
Emerging Markets	**0.98**	**0.58**
	(2.41)	**(2.26)**

Table 11. Univariate Portfolios of Hedge Funds Sorted by *MAX* for Funds with Low and High Leverage/Derivates Usage

A total of 8,010 individual hedge funds are first sorted based on their leverage and derivatives usage to generate two subsamples: a subsample of 400 hedge funds (approximately 5% of the total sample) to detect the funds with low leverage and derivatives usage; and another subsample of 400 hedge funds to detect the funds with high leverage and derivatives usage. Then, for each subsample, quintile portfolios are formed separately every month from January 1995 to December 2014 by sorting these 400 hedge funds based on their *MAX*. In each panel, Quintile 1 is the portfolio of hedge funds with the lowest *MAX*, and quintile 5 is the portfolio of hedge funds with the highest *MAX*. The table reports the next month average returns and the 9-factor alphas for each quintile. The last row shows the average monthly raw return difference and the 9-factor alpha difference between High *MAX* and Low *MAX* quintiles. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the returns and alphas.

Panel A. Funds with Low Leverage and Derivatives Usage

Quintiles	Next Month Average Returns	Next Month 9-Factor Alphas
Q1	0.14	–0.01
	(1.06)	(–0.10)
Q2	0.17	0.00
	(1.16)	(0.01)
Q3	**0.34**	0.22
	(2.05)	(1.35)
Q4	**0.34**	0.16
	(1.89)	(1.00)
Q5	0.41	0.25
	(1.69)	(1.06)
Q5 – Q1	0.27	0.26
t-statistic	(1.43)	(1.14)

Panel B. Funds with High Leverage and Derivatives Usage

Quintiles	Next Month Average Returns	Next Month 9-Factor Alphas
Q1	–0.04	–0.05
	(–0.42)	(–0.65)
Q2	**0.37**	**0.37**
	(3.76)	**(3.64)**
Q3	**0.43**	**0.37**
	(4.37)	**(4.08)**
Q4	**0.54**	**0.39**
	(3.93)	**(3.15)**
Q5	**0.81**	**0.68**
	(4.33)	**(3.58)**
Q5 – Q1	**0.85**	**0.74**
t-statistic	**(4.76)**	**(3.68)**

Table 12. Market- and Macro-timing Tests of Individual Hedge Funds

This table investigates the market- and macro-timing ability of non-directional, semi-directional, and directional hedge funds. Market-timing ability is tested using the excess market return (*MKT*), and macro-timing ability is tested using the Economic Uncertainty Index (*UNC*) of Bali, Brown, Caglayan (2014). For each analysis, individual hedge fund excess returns are regressed on the excess market return and the economic uncertainty index separately as well as on the index implying market- and macro-timing ability using pooled panel regressions for the sample period January 1995–December 2014. Market and macro-timing ability of hedge funds is tested using a model similar to Henriksson and Merton (1981):

$$R_{i,t} = \alpha + \beta_1 \cdot Y_t + \beta_2 \cdot Y_t^{high} + \varepsilon_{i,t} \,,$$

where $R_{i,t}$ is excess return of fund i in month t, Y_t is the excess market return in month t for the market-timing test, and the economic uncertainty index of Bali et al. in month t for the macro-timing test, and Y_t^{high} is variable implying market-timing ability for the market-timing test, and the economic uncertainty index implying macro-timing ability for the macro-timing test:

$$Y_t^{high} = \begin{Bmatrix} Y_t & \text{if } Y_t \text{ is higher than its time-series median} \\ 0 & \text{otherwise} \end{Bmatrix}.$$

In this regression specification, a positive and significant value of β_2 implies superior market- and macro-timing ability of individual hedge funds. For the *t*-statistics reported in parentheses, clustered robust standard errors are estimated to account for two dimensions of cluster correlation (fund and year). This approach allows for correlations among different funds in the same year as well as correlations among different years in the same fund. Numbers in bold denote statistical significance.

	Non-Directional Hedge Funds	Semi-Directional Hedge Funds	Directional Hedge Funds
β_2 from using *MKT* in the market-timing estimation	–0.050 (–0.80)	**0.169** **(2.07)**	**0.277** **(2.62)**
β_2 from using *UNC* in the macro-timing estimation	0.101 (0.93)	**0.494** **(2.32)**	**0.894** **(2.58)**

Table 13. Univariate Portfolios of Hedge Funds Sorted by *MAX* for Funds with Low and High Market-timing Ability

A total of 8,010 individual hedge funds are first sorted based on their market-timing coefficients from Eq. (4) to generate two subsamples: a subsample of 400 hedge funds (approximately 5% of the total sample) to detect the funds with low market-timing ability; and another subsample of 400 hedge funds to detect the funds with high market-timing ability. Then, for each subsample, quintile portfolios are formed separately every month from January 1995 to December 2014 by sorting these 400 hedge funds based on their *MAX*. In each panel, Quintile 1 is the portfolio of hedge funds with the lowest *MAX*, and quintile 5 is the portfolio of hedge funds with the highest *MAX*. The table reports the next month average returns and the 9-factor alphas for each quintile. The last row shows the average monthly raw return difference and the 9-factor alpha difference between High *MAX* and Low *MAX* quintiles. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the returns and alphas.

Panel A. Funds with Low Market-timing Ability

Quintiles	Next Month Average Returns	Next Month 9-Factor Alphas
Q1	0.02	–0.12
	(0.20)	(–1.01)
Q2	0.15	0.01
	(1.12)	(0.09)
Q3	**0.34**	**0.24**
	(2.37)	**(1.74)**
Q4	**0.33**	0.17
	(1.85)	(0.92)
Q5	0.32	0.09
	(1.32)	(0.36)
Q5 – Q1	0.30	0.21
t-statistic	(1.56)	(0.86)

Panel B. Funds with High Market-timing Ability

Quintiles	Next Month Average Returns	Next Month 9-Factor Alphas
Q1	0.06	0.17
	(0.37)	(0.76)
Q2	**0.53**	**0.62**
	(2.45)	**(2.04)**
Q3	**0.65**	**0.85**
	(2.65)	**(2.58)**
Q4	**0.77**	**0.86**
	(2.87)	**(2.40)**
Q5	**0.97**	**1.08**
	(2.48)	**(2.06)**
Q5 – Q1	**0.91**	**0.91**
t-statistic	**(2.55)**	**(2.11)**

Upside Potential of Hedge Funds as a Predictor of Future Performance

Turan G. Bali, Stephen J. Brown, and Mustafa O. Caglayan

Online Appendix

To save space in the paper, we present some of our findings in the Online Appendix. Section I describes the Lipper Trading Advisor Selection System (TASS) database. Section II provides the risk factors used in the estimation of the risk-adjusted returns (alphas) of *MAX*-sorted portfolios. Section III discusses average portfolio characteristics of hedge funds in *MAX*-sorted portfolios. Section IV provides a detailed analysis of the interaction between *MAX* and volatility. Section V examines the predictive power of *MAX* and the appraisal/Sharpe ratio based on the independently sorted 5×5 bivariate portfolios. Section VI provides subsample analyses. Section VII investigates the effect of outliers in returns on the predictive power of *MAX*. Section VIII provides evidence from mutual funds by replicating our main analyses for the mutual fund industry.

Table I presents summary statistics of invidual hedge funds obtained from the TASS database. Table II reports the cross-sectional averages of various characteristics of funds in each *MAX*-sorted quintile. Table III reports results from univariate portfolios of hedge funds sorted by alternative measures of *MIN*. Table IV shows 5x5 conditional (sequentially) sorted bivariate quintile portfolio analysis of *MAX* and STDEV. Table V reports results from sorting individual hedge funds into univariate quintile portfolios based on their *MAX*/STDEV ratios. Table VI shows results from 5x5 independently sorted bivariate quintile portfolios of *MAX* and the appraisal ratio. Table VII reports results from 5x5 independently sorted bivariate quintile portfolios of *MAX* and the Sharpe ratio. Table VIII reports subsample analysis from Fama-MacBeth cross-sectional regressions of next month returns on *MAX* with and without control variables. Table IX presents the univariate quintile portfolio results of *MAX* after winsorizing hedge fund returns at the 1% and 99% level each month cross-sectionally. Table X shows results from the univariate portfolios of hedge funds sorted by *MAX* into 5, 10, 20, and 50 portfolios separately. Table XI presents the sample and rank order correlations between *MAX* and alternative performance measures such as alpha, appraisal ratio, and Sharpe ratio. Table XII reports summary statistics for the mutual funds database. Table XIII investigates whether upside potential (*MAX*) predicts the cross-sectional variation in future mutual fund returns and tests whether mutual funds have the ability to time fluctuations in the equity market and macroeconomic fundamentals.

I. Hedge Fund Database

This study uses monthly hedge fund data from the Lipper Trading Advisor Selection System (TASS) database. Table I of this Online Appendix provides summary statistics on hedge fund numbers, returns, AUM, and fee structures for the sample of 11,099 hedge funds. For each year, Panel A of Table 1 reports the number of funds entering the database, the number of funds dissolved, total AUM at the end of each year (in billions of dollars), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolio. One important characteristic about TASS is that it includes no defunct funds prior to 1994. Therefore, in an effort to mitigate potential survivorship bias in the data, we select 1994 as the start of our sample period and employ our analyses on hedge fund returns for the period January 1994 to December 2014.

Table I, Panel A, reports a sharp reversal in the growth of hedge funds in both numbers and AUM since the end of 2007, the starting point of the last worldwide financial crisis. The AUM in our database increased exponentially from a small $55 billion in 1994 to $892 billion in 2007 and the number of operating hedge funds increased almost seven times to 5,275 in December 2007, from 748 in January 1994. However, both these figures reversed course beginning in 2008, the start of the worldwide financial crisis; the number of operating hedge funds fell sharply to below 2,500, while total AUM dropped by more than half, to $405 billion, by the end of December 2014. In addition, the yearly attrition rates in Panel A of Table 1 (ratio of the number of dissolved funds to the total number of funds at the beginning of the year) paints a similar picture: From 1994 to 2007, on average, the annual attrition rate in the database was only 8.1%; between 2008 and 2014, however, this annual figure increased by almost 2.4 times to 19.4%. These statistics simply reflect the severity of the financial crisis of the past seven years. In 2008 and 2011 alone, for example, hedge funds, on average, lost 1.56% and 0.48% (return) per month, respectively.

Panel B of Table I reports the cross-sectional mean, median, standard deviation, minimum, and maximum values for certain hedge fund characteristics for the period January 1994 to December 2014. One interesting point evident in Panel B is the short lifespan of hedge funds. The median age (number of months in existence since inception) is only 60 months, equivalent to five years. This short lifespan is mostly due to the fact that hedge fund managers must first cover all losses from previous years before getting paid in the current year. This forces hedge fund managers to dissolve quickly and form new hedge funds after a bad year instead of trying to cover losses in subsequent years. Another remarkable observation that can be detected from this panel is the large size disparity among hedge funds. When we measure fund size as average monthly AUM over the life of the fund, we see that the mean hedge fund size is $85.7 million, while the median hedge fund size is only $40.0 million. This suggests that only a few hedge funds have very large AUM in our database, which reflects true hedge fund industry conditions.

We also report the distributional moments of hedge fund returns. For each fund in our sample from January 1994 to December 2014, we compute the volatility, skewness, and excess kurtosis of monthly hedge fund returns and then test whether these high-order moments are significantly different from zero based on the time-series distribution of hedge fund returns. Panel C of Table I in the Online Appendix shows that among 8,010 hedge funds that have a minimum of 24 monthly return observations, all of them have significant volatility at the 10% level or better. In addition, 2,888 funds exhibit positive skewness and 5,122 funds exhibit negative skewness. Among the funds with positive (negative) skewness, 50.3% (63.8%) are statistically significant at the 10% level. Finally, the majority of hedge funds (7,118 funds) exhibit positive excess kurtosis and among these funds, 74.8% are statistically significant at the 10% level. We also conduct the Jarque-Bera (JB) normality test and the last column of Panel C in Table I shows that 70.3% of the funds in our sample exhibit significant JB statistics, rejecting the null hypothesis of normality at the 10% level.[24]

Lastly, hedge fund studies can be subject to potential data bias issues. Brown, Goetzmann, Ibbotson, and Ross (1992), Fung and Hsieh (2000), Liang (2000), and Edwards and Caglayan (2001) cover these well-known data bias problems extensively in the hedge fund literature. The first potential data bias in a hedge fund study is the survivorship bias if the database does not include the returns of non-surviving hedge funds. In our study, for the period January 1994 to December 2014, we have the monthly return histories of 2,415 funds in the live funds (survivor) database and 8,684 funds in the graveyard (defunct) database. We estimate that if the returns of non-surviving hedge funds (graveyard database) had been excluded from the analyses, there would have been a survivorship bias of 2.70% in average annual hedge fund returns. This is the difference between the annualized average return of only surviving funds in the sample and the annualized average return of all surviving and non-surviving funds in the sample.[25] However, the fact that we also use the returns of defunct funds in our analyses removes any potential concerns about the effect of survivorship bias on our main findings.

Another important data bias in hedge fund studies is called the back-fill bias. Once a hedge fund is included in a database, that fund's previous returns are automatically added to that database as well (a process called "back-filling"). This practice, however, in the hedge fund industry is problematic, because it generates an incentive only for successful hedge funds to report their initial returns to the database vendor and, as a result, it can generate an upward bias in the returns of newly reporting hedge funds during their early histories. In the TASS database we have information on when a hedge fund is added to the database as well as the fund's first reported performance date. On average, there is a one-year gap between the first performance date and the date that the fund is added to the database, with the latter coming one year after the former. We check whether this one-year gap generates a difference in returns between funds' first year performance vs. the rest of period performance (the rest of period performance starts from the 13th month until either the fund is deceased or until the end of our sample December 2014). We find that the cross-sectional average of the funds' time-series monthly return average during the first year of existence is 0.67% higher than the cross-sectional average of the funds' time-series monthly return average in the subsequent period. Fung and Hsieh (2000) also find a similar back-fill bias in hedge fund returns and delete

[24] For 66.0% (60.0%) of the funds in our sample, the JB statistics are significant at the 5% (1%) level, rejecting the null hypothesis of normality.

[25] This finding is comparable to earlier studies of hedge funds. Liang (2000) reports an annual survivorship bias of 2.24% and Edwards and Caglayan (2001) report an annual survivorship bias of 1.85%.

the first 12-month returns of all individual hedge funds in their sample. Following Fung and Hsieh, to avoid back-fill bias in our analyses, we also delete the first 12-month return histories of all individual hedge funds in our database.[26]

The last possible data bias in a hedge fund study is called the multiperiod sampling bias. Investors generally ask for a minimum of 24 months of return history before making a decision whether to invest in a hedge fund or not. Therefore, in a hedge fund study, the inclusion of hedge funds with return histories shorter than 24 months would be misleading to those investors who seek past performance data to make future investment decisions. In addition, a minimum 24-month return history requirement makes sense from a statistical perspective to be able to run regressions and obtain sensible estimates of alphas, betas, Sharpe ratios, and appraisal ratios for individual hedge funds in the sample. Therefore, we require all hedge funds in the sample to have at least 24 months of return history. This 24-month minimum return history requirement, however, decreases our sample size from 10,442 to 8,010 funds (i.e., 2,432 funds in the sample have return histories of less than 24 months). There is a slight chance of introducing a new survivorship bias into the system due to the deletion of these 2,432 hedge funds from the sample (funds that had return histories of less than 24 months most probably dissolved due to bad performance). In an effort to find the impact of these deleted 2,432 hedge funds on total hedge fund performance, we compare the performance of hedge funds *before* and *after* the 24-month return history requirement. We find that the annual average return of hedge funds that pass the 24-month requirement (8,010 funds) is only 0.44% higher than the annual average return of all hedge funds (10,442 funds) in the sample. This difference between the two samples is a small, insignificant percentage in terms of survivorship bias considerations.[27]

II. Risk Factors

We rely on the widely accepted nine factors when computing the risk-adjusted return of *MAX*-sorted hedge fund portfolios. Specifically, we use the market, size, book-to-market, and momentum factors of Fama and French (1993) and Carhart (1997) as well as the five trend-following factors of Fung and Hsieh (2001) for currencies, bonds, commodities, short-term interest rates, and stock indexes. The market factor (MKT) of Fama and French is the value-weighted NYSE/AMEX/NASDAQ—according to the Center for Research in Security Prices (CRSP)—market index return in excess of the risk-free rate (one-month T-bill rate). The size factor (SMB) is the return of a zero-cost long-short size-based portfolio that is long stocks with low market capitalization and short stocks with high market capitalization. The book-to-

[26] Deleting the first 12-month returns results in deleting 657 funds from our sample because they have return histories less than 12 months, bringing the total number of hedge funds in our database to 10,442 from 11,099. There is a a slight chance that deletion of these funds may introduce a new survivorship bias into the system (funds that had return histories less than 12 months most probably dissolved due to bad performance; therefore the returns of the remaining 10,442 funds might be higher than the returns of the original 11,099 funds). We find, however, contrary to our expectations, that the average annual returns of 10,442 funds is in fact 0.79% lower than the average annual returns of 11,099 funds, suggesting no evidence of inclusion of an upwardly biased returns into our analyses.

[27] This figure is similar to estimates from earlier studies. Edwards and Caglayan (2001) also impose a 24-month return history requirement and find a small survivorship bias estimate of 0.32%. Fung and Hsieh (2000), on the other hand, impose a 36-month return history requirement and find the survivorship bias estimate to be 0.60%.

market factor (HML) of Fama and French is the return of a zero-cost long-short book-to-market ratio-based portfolio that is long stocks with high book-to-market ratios and short stocks with low book-to-market ratios. The momentum factor (MOM) of Carhart (1997) is the return of a portfolio that is long stocks with high momentum and short stocks with low momentum. Fung and Hsieh's (2001) currency trend-following factor (FXTF) is measured as the return of a primitive trend-following strategy (PTFS) currency lookback straddle; the bond trend-following factor (BDTF) is measured as the return of a PTFS bond lookback straddle; the commodity trend-following factor (CMTF) is measured as the return of a PTFS commodity lookback straddle; the short-term interest rate trend-following factor (IRTF) is measured as the return of a PTFS short-term interest rate lookback straddle; and the stock index trend-following factor (SKTF) is measured as the return of a PTFS stock index lookback straddle.[28]

III. Average Portfolio Characteristics of *MAX*-sorted Quintiles

To obtain a clearer picture of the composition of the *MAX*-sorted portfolios, Table II of this Online Appendix presents average characteristics of hedge funds for each of the five quintiles, averaged across the sample period from January 1995 to December 2014. We report average values for the sort variable (the maximum return over the past 12 months denoted by *MAX*), as well as the *MIN*, the past 12-month return (*AVRG*), the past 12-month standard deviation (*STDEV*), the past one-month return (*LagRet*), and fund characteristics *Size*, *Age*, *Flow*, *IncentFee*, *MgtFee*, *MinInvest*, *Redemption*, *DLockup*, and *DLever*.

Table II shows that the high-*MAX* funds with stronger upside potential exhibit higher *MIN*, higher average 12-month returns, higher 12-month standard deviations, higher past one-month returns, higher incentive fees, higher management fees, larger fund flows, lower minimum investment amounts, a lower redemption period, and more frequent usage of leverage. However, there is no clear pattern between *MAX* and fund size, fund age, or lockup. These average portfolio characteristics economically make sense because funds with stronger upside potential (on average) outperform funds with weaker upside potential. The ability of the high-*MAX* funds to produce higher returns motivates them to charge higher management and incentive fees to their clients, compared to the low-*MAX* funds. The high-*MAX* funds also attract more capital. This suggests that clients of funds with stronger upside potential are indeed willing to pay higher fees and invest more in the high-*MAX* funds under the expectation of obtaining higher returns in the future. The findings in Table II also suggest that the high-*MAX* funds make more frequent use of dynamic trading strategies with extensive usage of derivatives and leverage, which may enable them to possess better market-timing and macro-timing abilities. Lastly, as expected, the monthly returns of the high-*MAX* funds have higher volatility than those of the low-*MAX* funds.

[28] The monthly returns on four factors of Fama-French-Carhart are obtained from Kenneth French's online data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html. The five trend-following factors of Fung and Hsieh (2001)—FXTF, BDTF, CMTF, IRTF, and SKTF—are provided by David Hsieh at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

IV. Detailed Analysis of the Interaction between *MAX* and *STDEV*

In this section, we provide a detailed analysis of the interaction between *MAX* and volatility. As shown in Table II of this Online Appendix, hedge funds with a high *MAX* also have a high standard deviation of monthly returns. Thus, one may wonder if *MAX* is just another proxy for volatility and whether the predictive power of *MAX* is subsumed at the presence of standard deviation of hedge fund returns. To address this issue, in Table IV of this Online Appendix, we conduct a 5×5 conditional (sequentially) sorted bivariate portfolio analysis of *MAX* and *STDEV*. Specifically, hedge funds are first sorted into quintile portfolios based on *STDEV* and then, within each *STDEV* quintile, hedge funds are further sorted into sub-quintiles based on their *MAX*. The last column in Table IV shows that, moving from the low-*MAX* to the high-*MAX* quintile, the next-month average return on *MAX*-sorted portfolios (averaged across the *STDEV* quintiles) increases monotonically. After the standard deviation of monthly returns is controlled for, the average return and alpha spreads between the high-*MAX* and low-*MAX* quintiles are 0.69% and 0.68% per month, respectively, and highly significant, with Newey-West (1987) *t*-statistics of 5.71 and 5.00, respectively.

Table IV also shows that, within all quintiles of *STDEV*, the average return spreads between the high-*MAX* and low-*MAX* quintiles are economically large, ranging from 0.55% to 1.07% per month, and highly significant, with *t*-statistics ranging from 3.45 to 8.23. The corresponding alpha spreads between the high-*MAX* and low-*MAX* quintiles are also economically large and highly significant within all *STDEV* quintiles, in the range of 0.54 to 1.12% per month, with *t*-statistics ranging from 3.17 to 7.78. This result clearly shows that controlling for *STDEV* does not affect the significant predictive power of *MAX* on future fund returns.

Lastly, to control for the effect of *STDEV* on *MAX* at the fund level, we introduce an alternative measure where we scale upside potential of each fund with the standard deviation of hedge fund returns, *MAX*/*STDEV*. Three alternative measures of *MAX*/*STDEV* ratios are generated: *MAX12*/*STDEV12* ratio generated from 12 month returns, *MAX24/STDEV24* ratio generated from 24 month returns, and *MAX36/STDEV36* ratio generated from 36 month returns. For each month, from January 1995 to December 2014, we form quintile portfolios by sorting individual hedge funds based on their *MAX*/*STDEV* ratios. The first column in Table V of this Online Appendix shows that, moving from quintile 1 to quintile 5, the next-month average return on the *MAX12/STDEV12*-sorted portfolios increase monotonically, leading to economically and statistically significant returns and alpha spreads between the high-*MAX/STDEV* and low-*MAX/STDEV* quintiles. Specifically, the average return and 9-factor alpha spreads between quintiles 5 and 1 are economically large, 0.59% and 0.68% per month, respectively, and highly significant, with Newey-West *t*-statistics of 4.42 and 5.17, respectively. Similar results are obtained from *MAX24/STDEV24* and *MAX36/STDEV36*. Overall, these results provide evidence that *MAX*'s predictive power is not subsumed even after controlling for volatility at the fund level.

V. Independent Bivariate Sorts of *MAX* and the Appraisal/Sharpe Ratios

Table VI of this Online Appendix examines the predictive power of *MAX* and the 9-factor appraisal ratio based on the independently sorted 5×5 bivariate portfolios. After the appraisal ratio is controlled for, the raw return and alpha spreads between the high-*MAX* and low-*MAX* quintiles are economically large, 0.73% and 0.56% per month, respectively, and highly statistically significant, with *t*-statistics of 3.63 and 2.91, respectively. In addition, within all *AR* quintiles, the average return and alpha spreads between the high-*MAX* and low-*MAX* quintiles are also positive and highly significant, without an exception. Table VI also shows that, after *MAX* is controlled for, the raw return and alpha spreads between the high-*AR* and low-*AR* quintiles are economically large, 0.52% and 0.61% per month, respectively, and highly significant, with *t*-statistics of 5.76 and 7.02, respectively. In addition, within all *MAX* quintiles, the average return and alpha spreads between the high-*AR* and low-*AR* quintiles are also positive and highly significant, without an exception. These results clearly show that controlling for the appraisal ratio (*MAX*) does not affect the significant predictive power of *MAX* (appraisal ratio) on future fund returns, suggesting that *MAX* is a good complementary measure to appraisal ratio in assessing the cross-sectional variation among fund returns to detect superior future hedge fund performance.

Table VII of this Online Appendix investigates the predictive power of *MAX* and the Sharpe ratio based on the independently sorted 5×5 bivariate portfolios and provides very similar results to those reported in Table 4 (of the main paper) and Table VI (of the Online Appendix); controlling for the Sharpe ratio (*MAX*) does not change the significant predictive power of *MAX* (Sharpe ratio) on future fund returns. These results support our interpretation of *MAX* as a complementary measure to Sharpe ratio as well in detecting superior future hedge fund returns.

Overall, the results in Table 4 in the main paper, and Table VI and Table VII in the Online Appendix indicate that our measure of upside potential (*MAX)* and traditional measures of performance have some distinct characteristics that are orthogonal to each other, and hence their predictive power is not subsumed by one another.

VI. Subsample Analyses

The cross-sectional regression results checking *MAX*'s predictive power over future hedge fund returns, which is reported in Table 6 of our main paper, are based on the 20-year sample period from January 1995 to December 2014. We now investigate whether the predictive power of *MAX* remains intact during subsample periods. We conduct subsample analysis by dividing the full sample into two and then examining the significance of *MAX* for the first decade (January 1995 to December 2004) and second decade (January 2005 to December 2014) separately. In addition to these two subsample periods, we examine the predictive power of *MAX* during high and low economic activity periods (i.e., good versus bad states of the economy). We determine increases and decreases in economic activity by relying on the Chicago Fed National Activity (CFNAI) index, which is a monthly index designed to assess overall economic activity and related inflationary pressure. The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward the trend growth rate over time, a positive index reading corresponds to growth above the trend and a negative index reading corresponds to growth below the trend.[29]

We perform subsample analyses based on the Fama-MacBeth cross-sectional regressions. Panel A of Table VIII in this Online Appendix shows that, for the first half of our sample, the average slope on *MAX* is positive and highly significant in both univariate and multivariate regressions. The average slope from the monthly univariate regressions of one-month-ahead returns on *MAX* alone is 0.036, with a Newey-West *t*-statistic of 2.29. After controlling for a large set of fund characteristics, past return, volatility, and risk-adjusted returns, we find the average slope on *MAX* remains positive, at 0.044, with a *t*-statistic of 2.18. These two average slopes (0.036 and 0.044) for the period 1995–2004 represent an economically significant increase of 0.60% and 0.74% per month, respectively, in the average fund's expected return for moving from the first to the fifth quintile of *MAX*.

Panel B of Table VIII shows that the predictive power of *MAX* persists in the second half of our sample as well. Specifically, the average slope on *MAX* has a larger magnitude of 0.048 in univariate regressions and higher statistical significance, with a Newey-West *t*-statistic of 2.66. After controlling for the same set of variables, we find the average slope on *MAX* also remains positive at 0.036, with a *t*-statistic of 2.49. We find that the economic significance of these two average slopes (0.048 and 0.036) for the period 2005–2014 corresponds to a 0.56% and 0.42% per month increase, respectively, in the average fund's expected return when moving from the first to the fifth quintile of *MAX*. The results in Panels A and B of Table VIII indicate that funds with higher upside potential are able to produce superior future returns during both subsample periods.

We now present the Fama-MacBeth regression results during good and bad states of the economy, separately. In Panel C of Table VIII, monthly cross-sectional regressions are estimated only for those months when the CFNAI index is positive on a given month during the period January 1995 to December 2014. Panel C shows that, for good states of the economy (CFNAI > 0), the average slope on *MAX* is positive and highly significant in univariate regressions and after accounting for the control variables. The average slope from the monthly univariate regressions of one-month-ahead returns on *MAX* alone is 0.042, with a *t*-statistic of 2.66. After controlling for a large set of fund characteristics, past return, volatility, and risk-adjusted returns, we find the average slope on *MAX* remains positive, at 0.043, with a *t*-statistic of 2.44. These two average slopes (0.042 and 0.043) for good states of the economy represent an economically significant increase of 0.60% and 0.61% per month, respectively, in the average fund's expected return for moving from the first to the fifth quintile of *MAX*.

Panel D of Table VIII examines the predictive power of *MAX* during low economic activity for those months when the CFNAI index is negative. During bad states of the economy (CFNAI < 0), the

[29] The 85 economic indicators that are included in the CFNAI are drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. Each of these data series measures some aspect of overall macroeconomic activity. The derived index provides a single summary measure of a factor common to these national economic data.

average slope on *MAX* in univariate regressions is again positive and statistically significant, at 0.042, with a *t*-statistic of 3.10. After controlling for the same set of variables, we find the average slope on *MAX* remains significantly positive, at 0.037, with a *t*-statistic of 2.53. We find that the economic significance of these two average slopes (0.042 and 0.037) during bad states of the economy corresponds to a 0.60% and 0.53% per month increase, respectively, in the average fund's expected return when moving from the first to the fifth quintile of *MAX*. Overall, the results in Panels C and D of Table VIII provide evidence that hedge funds with stronger upside potential are able to perform better than those funds with weaker upside potential during both good and bad states of the economy.

Despite large fluctuations observed in the risk, return, and upside potential of hedge funds during these four subperiods, Panels A through D of Table VIII provide evidence of a positive and significant relation between *MAX* and future fund returns in all subsample periods analyzed. These results clearly show that, with and without controlling for a large set of variables, upside potential is an important determinant of the cross-sectional dispersion in hedge fund returns for all states of the economy, including expansionary and contractionary periods.

VII. Effect of Outliers in Returns on the Predictive Power of *MAX*

In this section, we investigate the effect of outliers in returns on the predictive power of *MAX*. Specifically, we use winsorization, which sets all outliers to a specified percentile of the data to reduce the impact of possibly spurious outliers. For each month, we winsorize the monthly returns on individual hedge funds at the 1% and 99% levels. Then, we form quintile portfolios every month from January 1995 to December 2014 by sorting hedge funds based on their *MAX* values obtained from the winsorized data. Table IX of this Online Appendix shows that, from the winsorized data, the average return and alpha spreads between quintiles 5 and 1 are still positive and highly significant, at 0.71% per month (*t*-stat. = 3.43) and 0.46% per month (*t*-stat. = 2.38), respectively. These results are very similar to those reported in Panel B of Table 1 generated from the full return data. Hence, we conclude that the predictive power of *MAX* is not driven by outliers in returns.

We also test if there is information in extreme returns and in the extreme values of *MAX*. Specifically, we examine the predictive power of *MAX* in the cross section of larger numbers of portfolios that correspond to progressively larger cross-sectional spreads in *MAX*. For each month from January 1995 to December 2014, hedge funds are sorted based on their *MAX* into five, 10, 20, and 50 portfolios, separately. Table X of this Online Appendix presents the next-month average return difference and the next-month 9-factor alpha difference between the high-*MAX* and low-*MAX* portfolios. The results clearly show that, moving from five to 50 portfolios, the economic significance of the next-month average return and alpha spreads increases monotonically as the *MAX* spread between high-*MAX* and low-*MAX* portfolios increases. The average return spreads are 0.70% per month for five portfolios, 1.01% per month for 10 portfolios, 1.18% per month for 20 portfolios, and 1.50% per month for 50 portfolios. Similarly, the 9-factor alpha spreads are 0.47% per month for five portfolios, 0.75% per month for 10 portfolios, 0.91% per month for 20 portfolios, and 1.27% per month for 50 portfolios. More importantly, all return and alpha spreads are statistically significant, with *t*-statistics well above 2.00.

In sum, Table X shows that when we increase the number of portfolios that correspond to larger cross-sectional spreads in *MAX* between extreme portfolios, the outperformance of hedge funds with extremely high values of *MAX* becomes stronger with respect to funds with extremely low values of *MAX*. Overall, these results indicate significant information content in the extreme values of upside potential as well.

VIII. Evidence from Mutual Funds

An alternative way to explain the superior performance of the directional and semi-directional hedge funds with higher *MAX* values (relative to non-directional hedge funds) is to compare and contrast hedge funds with the mutual funds. Therefore, in this section, we provide evidence from mutual funds by replicating our main analyses for the mutual fund industry. First, we provide sumamry statistics for the mutual fund database. Second, we investigate whether our upside potential measure, *MAX*, can predict the future returns of mutual funds. Finally, we analyze whether mutual funds have the ability to time fluctuations in the equity market and macroeconomic fundamentals.

VIII.1. Mutual fund database

We use monthly returns of individual mutual funds from CRSP Mutual Fund database. Originally in our database there are 48,218 funds that report monthly returns at some point during our sample period from January 1994 to June 2013. Most of the mutual funds in the CRSP database, however, have multiple share classes designed for different client types. That is, a mutual fund may have a retail share class, an institutional share class, or a retirement share class. All of these share classes in essence constitute the same strategy, therefore their returns are highly correlated. However, the CRSP Mutual Fund database assigns a separate fund id number to each share class of the same fund, treating these share classes as if they are separate funds. In order to distinguish between share classes and funds, and not to use any duplicated funds (and hence returns) in our analyses, we first remove the multiple share classes of mutual funds from our study. We do this by keeping only the share class with the smallest fund id number (within a mutual fund family) in the database, and by removing the rest of the share classes of that particular mutual fund family from our analyses. This way, we make sure that each mutual fund family is represented with a single share class in our database. After removing multiple share classes, our sample size of mutual funds drops from 48,218 funds to 16,881 funds. That is, our database contains information on a total of 16,881 distinct, non-duplicated mutual funds, of which 7,073 are defunct funds and the remaining 9,808 are live funds. Table XII of this Online Appendix provides summary statistics both on numbers and returns of these single-share class, non-duplicated mutual funds. For each year, Table XII reports the number of funds entered into database, number of funds dissolved, attrition rate (the ratio of number of dissolved funds to the total number of funds at the beginning of the year), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted mutual fund portfolio.

The most notable point in Table XII is a sharp increase in the yearly attrition rates of mutual funds after year 2007, the starting point of the big worldwide financial crisis. From 1994 to 2007, on average, the annual attrition rate in the database was only 4.98%; however, this annual figure jumped to 10.56% in 2008 and to 9.63% in 2009 (the two highest figures detected in our sample period), giving an indication on how harsh the financial crisis is felt in the mutual fund industry in those years. In line with this jump in attrition rates, just during 2008, for example, mutual funds on average lost 2.67% (return) per month, generating the largest losses ever for their investors since the start of our analysis in 1994.

VIII.2. Does upside potential matter for mutual fund performance?

The primary differences between hedge funds and mutual funds are summarized as follows: (i) Hedge funds employ a range of investment tools, including derivatives, leverage, and short selling, whereas mutual funds tend to invest primarily on the long side, without extensively using other tools. The majority of mutual funds are long only, while hedge funds utilize much more aggressive dynamic trading strategies. (ii) Since hedge funds rely on hedging instruments and shorting techniques, they are more likely to outperform mutual funds in a down market. (iii) Mutual funds seek relative returns or those compared to a benchmark or index. A mutual fund's sole goal is to beat the benchmark. Therefore, if the index is down 10% but the mutual fund is down only 8%, this is considered a success. On the flip side, hedge funds seek absolute returns, not related to an index or benchmark performance. (iv) Hedge fund managers receive a performance fee at the end of the year, paid from investor gains. Mutual funds typically do not charge performance fees. The most common hedge fund fee structure is the 2/20: a 2% flat management fee skimmed off the top and a 20% fee on all profits. Most mutual funds charge less than 2% in total fees. (v) Hedge funds typically have lockup periods of at least one year; that is, each investment must remain in the hedge fund for at least one year (the lockup period). Withdrawals are permitted only with advance notice following the lockup period. Therefore, in difficult market periods or economic conditions, some hedge funds put up gates that restrict redemptions. On the other hand, investments in mutual funds are essentially liquid and are not impacted by lockups or gates.

The primary similarity between hedge funds and mutual funds is that both are managed portfolios. In other words, a manager or group of managers selects investments and adds them to a single portfolio. However, hedge funds are managed more aggressively than mutual funds are and have access to derivative instruments, leverage, and trading strategies inaccessible to mutual funds. With such an aggressive stance, hedge funds are in a better position to earn money, even when the market is falling. On the other hand, as Goetzmann, Ingersoll, Spiegel, and Welch (2007) observe, hedge funds can spuriously achieve high elevated abnormal risk-adjusted returns (alpha, appraisal ratio, and Sharpe ratio) at the expense of lower *MAX*.

From an investment style perspective, mutual funds can be viewed as highly regulated hedge funds with a larger number of investors and larger AUM. Since mutual funds do not use dynamic trading strategies with unique investment ideas, we do not expect cross-sectional differences in upside potential, *MAX*, to explain the cross-sectional dispersion in mutual fund returns. In fact, we should not expect mutual funds to exhibit wide cross-sectional dispersion in the *MAX* criterion, either. Along the same lines, we do not expect mutual funds to have significant market- or macro-timing ability as well.

To test these conjectures, we first test the predictive power of *MAX* over future mutual fund returns. Each month, from January 1995 to June 2013, we form quintile portfolios by sorting mutual funds based on their *MAX* values, where quintile 1 contains the mutual funds with the lowest *MAX* and quintile 5 contains the mutual funds with the highest *MAX*. Panel A of Table XIII shows the average *MAX* values and the next-month average returns on the *MAX*-sorted portfolios of mutual funds. The last row displays the difference for the average monthly return and the four-factor Fama-French-Carhart alpha between quintiles 5 and 1.

Table XIII, Panel A, shows that the average return difference between quintiles 5 and 1 is 0.49% per month, but statistically insignificant, with a *t*-statistic of 1.23. In addition, the risk-adjusted return spread turns out to be negative albeit insignificant. Specifically, the four-factor Fama-French-Carhart alpha difference between quintiles 5 and 1 is –0.18% per month, with a *t*-statistic of –1.61. This result indicates that mutual funds in the highest *MAX* quintile do not generate economically or statistically higher risk-adjusted returns than mutual funds in the lowest *MAX* quintile. Overall, the univariate portfolio results in Table XIII provide no evidence of a significant link between *MAX* and future returns on mutual funds, as dynamic portfolio strategies and leverage and derivative instruments do not play an important role in the mutual fund universe.

VIII.3. Market- and macro-timing ability of mutual funds

To test our second conjecture, we investigate the market- and macro-timing abilities of mutual funds with the same Henriksson–Merton (1981) model utilized in our earlier analysis for hedge funds. Panel B of Table XIII presents the estimated values of β_2 and the corresponding *t*-statistics for mutual funds. Essentially, pooled panel regressions are estimated for the sample period January 1995 to June 2013, this time using mutual fund excess returns as the dependent variable. The *t*-statistics reported in parentheses are again estimated using clustered robust standard errors, accounting for two dimensions of cluster correlation (fund and year). Table XIII, Panel B, shows that, for the equity market index, β_2 is statistically insignificant (coefficient of –0.037 with a *t*-statistic of –0.61), providing no evidence of market-timing ability for mutual funds. Similar results are obtained for the economic uncertainty index; β_2 is again statistically insignificant (coefficient of 0.609 with a *t*-statistic of 1.62), providing no evidence of macro-timing ability for mutual fund managers either.

Overall, the results show that directional and semi-directional hedge fund managers, by using derivatives and leverage, have the ability to actively vary their exposure to market risk and economic uncertainty up or down in a timely fashion according to macroeconomic conditions and the state of the financial markets. They can therefore generate higher *MAX*, and there exists a positive and stronger link between their *MAX* and their future hedge fund returns. On the other hand, for mutual funds, since they cannot exploit nonlinear payoff strategies available to hedge funds that take advantage of these conditions, there seems to be no evidence of a significant link between *MAX* and their future returns.

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Table I. Descriptive Statistics of Hedge Funds

There are total of 11,099 hedge funds that reported monthly returns to TASS. Panel A reports the number of hedge funds, total assets under management (AUM) at the end of each year by all hedge funds (in billion $s), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolio. Panel B reports for the sample period January 1994 – December 2014 the cross-sectional mean, median, standard deviation, minimum, and maximum statistics for hedge fund characteristics including returns, size, age, management fee, incentive fee, redemption period, and minimum investment amount. Panel C reports the time-series distribution of individual hedge fund returns (variance, skewness, excess kurtosis, and Jarque-Bera statistics) for 8,010 funds for which there are at least 24 months of return observations.

Panel A. Summary Statistics Year by Year

						Equal-Weighted Hedge Fund Portfolio Monthly Returns (%)				
Year	**Year Start**	**Entries**	**Dissolved**	**Year End**	**Total AUM (billion $s)**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
1994	748	276	17	1,007	55.0	-0.01	0.14	0.97	–1.58	1.12
1995	1,007	304	54	1,257	66.5	1.40	1.48	1.05	–0.94	3.14
1996	1,257	354	113	1,498	89.2	1.45	1.56	1.53	–1.65	4.00
1997	1,498	389	100	1,787	133.1	1.47	1.69	2.01	–1.56	4.79
1998	1,787	400	146	2,041	142.3	0.35	0.38	2.22	–5.14	3.05
1999	2,041	467	165	2,343	175.2	2.03	1.23	2.13	–0.34	6.43
2000	2,343	481	211	2,613	195.3	0.85	0.47	2.23	–2.01	5.45
2001	2,613	592	222	2,983	245.7	0.56	0.67	1.21	–1.64	2.64
2002	2,983	657	253	3,387	285.6	0.28	0.57	0.89	–1.47	1.49
2003	3,387	769	238	3,918	406.1	1.40	1.20	0.96	–0.20	3.43
2004	3,918	865	286	4,497	567.3	0.69	0.78	1.22	–1.33	2.89
2005	4,497	897	428	4,966	627.8	0.76	1.29	1.35	–1.51	1.99
2006	4,966	777	485	5,258	755.4	1.04	1.36	1.43	–1.63	3.42
2007	5,258	750	733	5,275	891.7	1.00	0.96	1.48	–1.73	3.11
2008	5,275	625	1,153	4,747	629.1	-1.56	-1.91	2.61	–6.14	1.81
2009	4,747	571	851	4,467	553.4	1.43	1.33	1.54	–0.90	4.76
2010	4,467	377	703	4,141	504.9	0.77	0.93	1.72	–2.92	3.13
2011	4,141	307	779	3,669	479.3	-0.48	-0.26	1.70	–3.59	2.07
2012	3,669	227	713	3,183	466.2	0.52	0.64	1.24	–2.15	2.48
2013	3,183	177	644	2,716	446.9	0.80	1.03	1.13	–1.71	2.74
2014	2,716	95	597	2,214	404.9	0.20	-0.26	0.82	–0.61	1.57

Table I (continued)

Panel B. Cross-Sectional Statistics of Hedge Fund Characteristics: January 1994 – December 2014

	N	Mean	Median	Std. Dev.	Minimum	Maximum
Average Monthly Return over the life of the Fund (%)	11,099	0.50	0.49	1.24	–25.14	25.47
Average Monthly AUM over the life of the Fund (million $)	11,099	85.7	40.0	233.8	0.5	7,835.1
Age of the Fund (# of months in existence)	11,099	73.4	60.0	54.0	1.0	252.0
Management Fee (%)	10,971	1.46	1.50	0.65	0.00	10.00
Incentive Fee (%)	10,847	15.40	20.00	7.79	0.00	50.00
Redemption Period (# of days)	11,099	37.1	30.0	32.9	0.0	365.0
Minimum Investment Amount (million $)	11,014	1.30	0.25	15.32	0.00	1,000.00

Panel C. Testing Normality of the Time-series Distribution of Individual Hedge Fund Returns

		Skewness		Excess Kurtosis		Normality
	Variance	Positive	Negative	Positive	Negative	Jarque-Bera Statistic
Total # of funds	8,010	2,888	5,122	7,118	892	8,010
% of funds significant at 10%	100.0%	50.3%	63.8%	74.8%	1.0%	70.3%
% of funds significant at 5%	100.0%	44.2%	57.9%	70.4%	0.1%	66.0%
% of funds significant at 1%	100.0%	33.4%	47.1%	62.8%	0.1%	60.0%

Table II. Average Fund Characteristics of *MAX* Quintile Portfolios

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *MAX* measure. *MAX* is the maximum monthly hedge fund returns over the last 12 months. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* measure and quintile 5 is the portfolio of hedge funds with the highest *MAX* measure. This table reports the average fund charactersitics of hedge funds for each of the five quintiles. *MIN* is the negative of the minimum monthly hedge fund returns over the last 36 months. AVRG is the past 12-month average return, STDEV is the past 12-month standard deviation, LagRet is the one-month lagged return, Size is measured as monthly assets under management in billions of dollars, Age is measured as the number of months in existence since inception, Flow is measured as the change in the assets under management from previous month to current month adjusted with fund returns and scaled with previous month's assets under management, IncentFee is a fixed percentage fee of the fund's annual net profits above a designated hurdle rate, MgtFee is a fixed percentage fee of assets under management, typically ranging from 1% to 2%, MinInvest is the minimum initial investment amount (measured in millions of dollars in the regression) that the fund requires from its investors to invest in a fund, Redemption is the minimum number of days an investor needs to notify a hedge fund before the investor can redeem the invested amount from the fund, DLockup is the dummy variable for lockup provisions (1 if the fund requires investors not to withdraw initial investments for a pre-specified term, usually 12 months, 0 otherwise), and DLever is the dummy variable for leverage (1 if the fund uses leverage, 0 otherwise).

	MAX	*MIN*	AVRG	STDEV	LagRet	Size	Age	Flow	IncentFee	MgtFee	MinInvest	Redemption	DLockup	DLever
Q1	1.67	4.35	0.22	1.12	–0.05	0.14	58.8	–0.21	12.9	1.34	1.69	42.4	0.20	0.49
Q2	3.04	5.33	0.41	1.79	0.17	0.15	59.5	–0.14	13.0	1.41	1.21	40.8	0.22	0.51
Q3	4.69	7.14	0.56	2.64	0.29	0.15	58.8	–0.09	14.8	1.46	1.08	37.0	0.23	0.56
Q4	7.39	9.80	0.82	3.97	0.52	0.13	58.9	0.09	16.8	1.49	0.83	33.2	0.25	0.62
Q5	15.88	15.14	1.61	7.57	1.32	0.10	59.9	0.11	17.9	1.58	0.64	29.9	0.24	0.66

Table III. Univariate Portfolios of Alternative *MIN* measures

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their alternative *MIN* measures. *MIN12*, *MIN24*, and *MIN36* represent the negative of the minimum monthly hedge fund returns over the last 12, 24, and 36 months, respectively. Quintile 1 is the portfolio of hedge funds with the lowest *MIN* measures, and quintile 5 is the portfolio of hedge funds with the highest *MIN* measures. In each column, the top panel reports the average *MIN* measures in each quintile, and the lower panel reports those same quintiles' next month average returns. The last two rows show the monthly average raw return differences and the 9-factor Alpha differences between quintile 5 (High *MIN* funds) and quintile 1 (low *MIN* funds). Average returns and Alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

	Average Size of *MIN12*	Average Size of *MIN24*	Average Size of *MIN36*
Q1	0.57	1.32	1.92
Q2	2.08	3.23	4.14
Q3	3.66	5.17	6.34
Q4	6.09	8.17	9.76
Q5	13.47	17.04	19.61
	Next-month returns of *MIN12* Quintiles	Next-month returns of *MIN24* Quintiles	Next-month returns of *MIN36* Quintiles
Q1	0.30	0.25	0.19
Q2	0.43	0.36	0.36
Q3	0.40	0.38	0.38
Q4	0.50	0.49	0.50
Q5	0.62	0.66	0.68
Q5 – Q1 Return Diff.	**0.31** **(1.79)**	**0.41** **(2.34)**	**0.49** **(2.88)**
Q5 – Q1 9-factor Alpha Diff.	0.24 (1.31)	**0.27** **(1.98)**	**0.39** **(2.11)**

Table IV. Bivariate Portfolios of *MAX* controlling for STDEV

This table presents 5x5 conditional (sequentially) sorted bivariate portfolio analysis of *MAX* and STDEV. Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds first based on the past 12-month standard deviation of returns (STDEV). Then, within each STDEV-sorted portfolio, hedge funds are further sorted into sub-quintiles based on their *MAX*. The last column presents the next-month returns of *MAX* quintile portfolios averaged across the STDEV quintiles. The last two rows show the monthly average return differences and the 9-factor alpha differences between High-*MAX* funds and Low-*MAX* funds within each STDEV quintile. Average returns and alphas are defined in monthly percentage terms. Newey-West *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

	Low STDEV	Q2	Q3	Q4	High STDEV	Averaged across STDEV quintiles
Low *MAX*	0.01	0.05	0.03	0.16	0.06	0.06
Q2	0.12	0.27	0.35	0.40	0.55	0.34
Q3	0.26	0.41	0.45	0.64	0.67	0.49
Q4	0.36	0.50	0.56	0.73	0.89	0.61
High *MAX*	0.57	0.60	0.70	0.76	1.13	0.75
Return Diff.	**0.56**	**0.55**	**0.67**	**0.60**	**1.07**	**0.69**
	(8.23)	**(6.17)**	**(5.60)**	**(3.45)**	**(4.05)**	**(5.71)**
Alpha Diff.	**0.57**	**0.54**	**0.62**	**0.57**	**1.12**	**0.68**
	(7.78)	**(4.26)**	**(4.83)**	**(3.17)**	**(3.33)**	**(5.00)**

Table V. Univariate Portfolios of Hedge Funds Sorted by *MAX/STDEV* Ratio

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *MAX/STDEV* ratios. Three alternative measures of *MAX/STDEV* ratios are generated: *MAX12/STDEV12* ratio generated from 12 month returns, *MAX24/STDEV24* ratio generated from 24 month returns, and *MAX36/STDEV36* ratio generated from 36 month returns. Univariate portfolios are formed for each of these alternative measures of *MAX/STDEV* ratio separately. Quintile 1 is the portfolio of hedge funds with the lowest *MAX/STDEV* ratio, and quintile 5 is the portfolio of hedge funds with the highest *MAX/STDEV* ratio. The table reports average *MAX/STDEV* ratio and the next month average returns in each quintile. The last two rows show the average monthly return difference and the 9-factor alpha difference between High-*MAX/STDEV* and Low-*MAX/STDEV* ratio quintiles. Average returns and alphas are defined in monthly percentage terms. Newey-West *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the returns and alphas.

	Average Size of *MAX12/STDEV12* Quintiles	Average Size of *MAX24/STDEV24* Quintiles	Average Size of *MAX36/STDEV36* Quintiles
Q1	1.19	1.48	1.65
Q2	1.67	1.96	2.15
Q3	1.99	2.28	2.47
Q4	2.35	2.65	2.87
Q5	3.28	3.52	3.76
	Next-month returns of *MAX12/STDEV12* Quintiles	Next-month returns of *MAX24/STDEV24* Quintiles	Next-month returns of *MAX36/STDEV36* Quintiles
Q1	0.05	0.20	0.23
Q2	0.40	0.39	0.43
Q3	0.55	0.50	0.46
Q4	0.61	0.53	0.50
Q5	0.64	0.51	0.47
Q5 – Q1 Return Diff.	**0.59** **(4.42)**	**0.31** **(2.61)**	**0.24** **(2.38)**
Q5 – Q1 9-factor Alpha Diff.	**0.68** **(5.17)**	**0.44** **(3.99)**	**0.34** **(3.31)**

Table VI. Independent Bivariate Sorts of *MAX* and the Appraisal Ratio (AR)

This table conducts an independently (simultaneously) sorted bivariate portfolio analysis of *MAX* and the appraisal ratio (AR). For each month from January 1996 to December 2014, we rank hedge funds according to their *MAX* and appraisal ratio independently at the same time and assign a quintile number (from 1 to 5, 1 being lowest category and 5 being highest category) to each individual hedge fund (for each *MAX* and *AR* category) based on its rankings. This generates 25 sub-quintiles of hedge funds, where each individual hedge fund is put in one of these 25 sub-quintiles depending on the hedge fund's rank within its peers with respect to its *MAX* and *AR* measure. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* (*AR*) within each *AR* (*MAX*) sorted quintile portfolio and Quintile 5 is the portfolio of hedge funds with the highest *MAX* (*AR*) within each *AR* (*MAX*) sorted quintile portfolio. The row "Average" presents the next-month returns of *MAX* quintile portfolios averaged across the *AR* quintiles. The column "Average" presents the next-month returns of *AR* quintile portfolios averaged across the *MAX* quintiles. The last two columns show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*MAX* funds) and quintile 1 (Low-*MAX* funds) within each *AR* quintile. The last two rows show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*AR* funds) and quintile 1 (Low-*AR* funds) within each *MAX* quintile. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

		MAX quintiles							
		Q1	Q2	Q3	Q4	Q5	Average	Q5–Q1 Ret Diff.	Q5–Q1 Alpha Diff.
AR quintiles	Q1	-0.31	0.02	0.19	0.22	0.49	0.12	**0.80 (3.32)**	**0.55 (2.12)**
	Q2	-0.08	0.21	0.35	0.47	0.57	0.30	**0.65 (2.81)**	**0.50 (2.05)**
	Q3	0.05	0.28	0.39	0.55	0.83	0.42	**0.78 (3.45)**	**0.62 (2.70)**
	Q4	0.15	0.38	0.46	0.68	0.86	0.51	**0.71 (3.29)**	**0.54 (2.63)**
	Q5	0.29	0.52	0.67	0.75	1.01	0.65	**0.72 (3.25)**	**0.58 (2.72)**
	Average	0.02	0.28	0.41	0.53	0.75		**0.73 (3.63)**	**0.56 (2.91)**
	Q5–Q1 Ret Diff.	**0.59**	**0.50**	**0.48**	**0.54**	**0.52**	**0.52**		
		(9.31)	**(7.58)**	**(5.56)**	**(3.91)**	**(2.19)**	**(5.76)**		
	Q5–Q1 Alpha Diff.	**0.61**	**0.56**	**0.51**	**0.72**	**0.65**	**0.61**		
		(8.34)	**(11.16)**	**(4.34)**	**(4.99)**	**(2.34)**	**(7.02)**		

Table VII. Independent Bivariate Sorts of *MAX* and the Sharpe Ratio (SR)

This table conducts an independently (simultaneously) sorted bivariate portfolio analysis of *MAX* and the Sharpe ratio (SR). For each month from January 1996 to December 2014, we rank hedge funds according to their *MAX* and Sharpe ratio independently at the same time and assign a quintile number (from 1 to 5, 1 being lowest category and 5 being highest category) to each individual hedge fund (for each *MAX* and *SR* category) based on its rankings. This generates 25 sub-quintiles of hedge funds, where each individual hedge fund is put in one of these 25 sub-quintiles depending on the hedge fund's rank within its peers with respect to its *MAX* and *SR* measure. Quintile 1 is the portfolio of hedge funds with the lowest *MAX* (*SR*) within each *SR* (*MAX*) sorted quintile portfolio and Quintile 5 is the portfolio of hedge funds with the highest *MAX* (*SR*) within each *SR* (*MAX*) sorted quintile portfolio. The row "Average" presents the next-month returns of *MAX* quintile portfolios averaged across the *SR* quintiles. The column "Average" presents the next-month returns of *SR* quintile portfolios averaged across the *MAX* quintiles. The last two columns show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*MAX* funds) and quintile 1 (Low-*MAX* funds) within each *SR* quintile. The last two rows show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*SR* funds) and quintile 1 (Low-*SR* funds) within each *MAX* quintile. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

		MAX quintiles							
		Q1	Q2	Q3	Q4	Q5	Average	Q5–Q1 Ret Diff.	Q5–Q1 Alpha Diff.
SR quintiles	Q1	-0.46	-0.09	0.05	0.05	0.11	-0.07	**0.57 (2.22)**	**0.51 (1.91)**
	Q2	-0.04	0.21	0.32	0.43	0.65	0.31	**0.69 (2.62)**	**0.59 (1.99)**
	Q3	0.13	0.33	0.40	0.57	0.83	0.45	**0.70 (2.94)**	**0.55 (2.23)**
	Q4	0.18	0.41	0.54	0.69	0.94	0.55	**0.76 (3.19)**	**0.57 (2.32)**
	Q5	0.32	0.57	0.73	0.94	1.44	0.80	**1.12 (4.77)**	**0.83 (3.31)**
	Average	0.02	0.29	0.41	0.54	0.79		**0.77 (3.95)**	**0.61 (2.97)**
	Q5–Q1 Ret Diff.	**0.78**	**0.66**	**0.68**	**0.88**	**1.32**	**0.86**		
		(5.23)	**(5.78)**	**(4.78)**	**(3.30)**	**(3.55)**	**(4.68)**		
	Q5–Q1 Alpha Diff.	**0.90**	**0.75**	**0.71**	**0.97**	**1.21**	**0.91**		
		(5.23)	**(7.00)**	**(5.47)**	**(4.68)**	**(4.53)**	**(6.29)**		

Table VIII. Fama-MacBeth Cross-sectional Regressions of Hedge Fund Returns on *MAX* and Control Variables: Subsample Analyses

This table reports the average intercept and average slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month-ahead hedge fund excess returns on *MAX* with and without control variables. The Fama-MacBeth regressions are run each month for the period January 1995–December 2014, and the average slope coefficients are calculated for two subsample periods (Panels A and B) and for good and bad states of the economy (Panels C and D). Newey-West *t*-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. Numbers in bold denote statistical significance of the average slope coefficients.

Intercept	*MAX*	*MIN*	SR	AVRG	STDEV	LagRet	Size	Age	Flow	IncentFee	MgtFee	MinInv	Redemption	DLockup	DLever
Panel A: First half of the full sample period (1995:01 – 2004:12)															
0.380	**0.036**														
(3.57)	**(2.29)**														
0.085	**0.044**	–0.010	0.078	**0.181**	0.071	**0.067**	–0.008	–0.002	–0.004	0.004	0.012	**0.006**	**0.003**	**0.100**	0.036
(0.20)	**(2.18)**	(–0.83)	(0.93)	**(2.64)**	(1.07)	**(3.26)**	(–0.13)	(–0.25)	(–1.26)	(1.21)	(0.19)	**(3.01)**	**(2.17)**	**(1.78)**	(0.98)
Panel B: Second half of the full sample period (2005:01 – 2014:12)															
0.037	**0.048**														
(0.25)	**(2.66)**														
–0.034	**0.036**	–0.006	**0.102**	**0.187**	0.081	**0.064**	**0.020**	–0.001	0.001	**0.003**	–0.001	**0.002**	0.001	0.041	0.014
(–0.31)	**(2.49)**	(–0.56)	**(4.84)**	**(3.01)**	(1.18)	**(3.35)**	**(1.87)**	(–0.07)	(0.95)	**(1.97)**	(–0.01)	**(2.52)**	(0.65)	(1.32)	(0.81)
Panel C: Good states of the economy (CFNAI > 0)															
0.394	**0.042**														
(4.46)	**(2.66)**														
0.173	**0.043**	–0.010	0.089	**0.171**	**0.096**	**0.041**	0.029	–0.003	0.001	0.002	–0.012	**0.005**	**0.002**	0.089	0.042
(0.53)	**(2.44)**	(–0.94)	(1.07)	**(1.93)**	**(1.86)**	**(2.36)**	(0.54)	(–0.39)	(0.50)	(0.80)	(–0.28)	**(2.45)**	**(2.69)**	(1.57)	(1.44)
Panel D: Bad states of the economy (CFNAI < 0)															
0.029	**0.042**														
(0.29)	**(3.10)**														
–0.118	**0.037**	–0.005	**0.091**	**0.196**	0.057	**0.088**	–0.017	0.001	–0.004	**0.005**	0.023	**0.003**	0.001	0.052	0.009
(–1.02)	**(2.53)**	(–0.60)	**(2.15)**	**(2.99)**	(1.00)	**(4.61)**	(–0.43)	(0.80)	(–1.44)	**(2.47)**	(0.55)	**(2.50)**	(0.90)	(1.24)	(0.33)

Table IX. Univariate Portfolios of Hedge Funds Sorted by *MAX* Using Winsorized Data

To avoid potential issues with outliers in returns, for each month, we winsorize the monthly returns on individual hedge funds at the 1% and 99% levels. Then, we form quintile portfolios every month from January 1995 to December 2014 by sorting hedge funds based on their *MAX* obtained from the winsorized data. Quintile 1 is the portfolio of hedge funds with the lowest *MAX*, and quintile 5 is the portfolio of hedge funds with the highest *MAX*. The table reports average *MAX* in each quintile, the next month average returns, and the 9-factor alphas for each quintile. The last row shows the average monthly raw return difference and the 9-factor alpha difference between High *MAX* and Low *MAX* quintiles. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the returns and alphas.

Quintiles	Average *MAX* in each Quintile	Next Month Average Returns	Next Month 9-Factor Alphas
Q1	1.68	0.09	–0.01
		(1.13)	(–0.14)
Q2	3.05	**0.33**	**0.20**
		(3.20)	**(2.56)**
Q3	4.69	**0.46**	**0.29**
		(3.64)	**(3.54)**
Q4	7.36	**0.58**	**0.32**
		(3.68)	**(3.17)**
Q5	13.68	**0.80**	**0.45**
		(3.10)	**(2.19)**
Q5 – Q1		**0.71**	**0.46**
t-statistic		**(3.43)**	**(2.38)**

Table X. Hedge Funds Sorted by *MAX* into 5, 10, 20 and 50 Portfolios

For each month from January 1995 to December 2014, hedge funds are sorted based on their *MAX* into 5, 10, 20, and 50 portfolios separately. Low *MAX* represents the portfolios with the lowest *MAX* in each analysis (whether 5, 10, 20 or 50 portfolios are created), and high *MAX* represents the portfolios with the highest *MAX* in each setup depending on whether 5, 10, 20, or 50 portfolios utilized in the analysis. This table reports the average monthly return difference and the 9-factor alpha difference between High *MAX* and Low *MAX* portfolios. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the return and alpha spreads between the High-*MAX* and Low-*MAX* portfolios.

	5 portfolios	*10 portfolios*	*20 portfolios*	*50 portfolios*
High *MAX* – Low *MAX* Return Diff.	**0.70**	**1.01**	**1.18**	**1.50**
t-statistic	**(3.48)**	**(3.79)**	**(3.75)**	**(4.14)**
High *MAX* – Low *MAX* Alpha Diff.	**0.47**	**0.75**	**0.91**	**1.27**
t-statistic	**(2.44)**	**(2.83)**	**(2.93)**	**(3.33)**

Table XI. Sample and Rank Correlations between *MAX* and Alternative Standard Measures of Performance

This table presents the average cross-sectional correlations between *MAX* and alternative standard performance measures; the 9-factor alpha, the 9-factor appraisal ratio, the Sharpe ratio. Panel A reports the sample cross-sectional correlations averaged across the months from January 1996 to December 2014. Panel B reports the cross-sectional rank-order correlations averaged across the months from January 1996 to December 2014.

Panel A. Sample Correlations

	Alpha	Appraisal Ratio	Sharpe Ratio	*MAX*
Alpha	1.000	0.532	0.221	0.223
Appraisal Ratio		1.000	0.695	-0.071
Sharpe Ratio			1.000	-0.056
MAX				1.000

Panel B. Rank-Order Correlations

	Alpha	Appraisal Ratio	Sharpe Ratio	*MAX*
Alpha	1.000	0.862	0.411	0.165
Appraisal Ratio		1.000	0.543	-0.073
Sharpe Ratio			1.000	-0.012
MAX				1.000

Table XII. Descriptive Statistics of Mutual Funds

There are total of 16,881 mutual funds that reported monthly returns to CRSP Mutual Fund Database for the years between 1994 and 2013 in this database, of which 7,073 are defunct funds and 9,808 are live funds. For each year from 1994 to 2013, this table reports the number of mutual funds, yearly attrition rates, and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted mutual fund portfolio.

						Equal-Weighted Mutual Fund Portfolio Monthly Returns (%)				
Year	Year Start	Entries	Dissolved	Year End	Attrition Rate (%)	Mean	Median	Std. Dev.	Minimum	Maximum
1994	3,108	625	132	3,601	4.25	-0.17	0.18	1.64	-3.08	2.00
1995	3,601	545	78	4,068	2.17	1.37	1.44	0.82	-0.33	2.41
1996	4,068	660	125	4,603	3.07	0.84	0.89	1.37	-2.15	2.98
1997	4,603	782	164	5,221	3.56	0.98	1.01	2.23	-2.31	4.01
1998	5,221	794	171	5,844	3.28	0.78	1.51	3.36	-8.29	3.67
1999	5,844	812	118	6,538	2.02	1.26	1.70	2.25	-2.34	5.16
2000	6,538	848	431	6,955	6.59	0.06	-1.26	3.16	-4.96	4.37
2001	6,955	649	520	7,084	7.48	-0.38	-0.17	3.60	-6.38	4.72
2002	7,084	480	506	7,058	7.14	-0.87	-1.00	3.00	-5.24	3.60
2003	7,058	477	472	7,063	6.69	1.62	1.14	1.98	-1.28	4.85
2004	7,063	469	381	7,151	5.39	0.74	1.25	1.69	-2.49	3.10
2005	7,151	635	485	7,301	6.78	0.52	0.94	1.62	-1.64	2.54
2006	7,301	765	405	7,661	5.55	0.88	1.07	1.52	-2.51	3.27
2007	7,661	946	445	8,162	5.81	0.53	0.65	1.81	-3.03	3.04
2008	8,162	1,971	862	9,271	10.56	-2.67	-1.31	5.05	-14.10	3.41
2009	9,271	1,232	893	9,610	9.63	2.01	2.84	4.46	-6.26	8.42
2010	9,610	946	539	10,017	5.61	1.07	1.69	3.66	-5.34	6.56
2011	10,017	1,134	634	10,517	6.33	-0.13	-0.55	3.51	-6.43	7.56
2012	10,517	510	932	10,095	8.86	0.92	1.08	2.31	-4.92	4.37
2013	10,095	445	732	9,808	7.25	0.77	0.76	1.72	-1.99	3.11

Table XIII. *MAX* and Mutual Fund Returns

Panel A. Average Raw and Risk-Adjusted Returns of *MAX* Quintile Portfolios

Quintile portfolios of mutual funds are formed every month from January 1995 to June 2013 by sorting mutual funds based on their *MAX*. Quintile 1 is the portfolio of mutual funds with the lowest *MAX* and quintile 5 is the portfolio of mutual funds with the highest *MAX*. Panel A reports average *MAX* in each quintile, the next month average returns, and the 4-factor alphas for each quintile. The last row of Panel A shows the average monthly raw return difference and the 4-factor alpha difference between High *MAX* and Low *MAX* quintiles. Average returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the returns and alphas.

Quintiles	Average *MAX* in each Quintile	Next Month Average Returns	Next Month 4-Factor Alphas
Q1	0.70	0.01	–0.00
		(0.26)	(–0.07)
Q2	2.73	0.21	0.03
		(1.67)	(0.28)
Q3	5.31	0.32	**–0.16**
		(1.22)	**(–1.94)**
Q4	7.59	0.47	–0.13
		(1.43)	(–1.52)
Q5	12.28	0.50	–0.18
		(1.22)	(–1.57)
Q5 – Q1		0.49	–0.18
t-statistic		(1.23)	(–1.61)

Panel B. Market- and Macro-timing Tests of Individual Mutual Funds

Market- and macro-timing ability of mutual funds is investigated by using pooled panel regressions of Henriksson-Merton (1981) and Bali, Brown, and Caglayan (2014) for the sample period January 1995–June 2013. A positive and significant value of β_2 implies superior market- and macro-timing ability of individual muutal funds. For the *t*-statistics reported in parentheses, clustered robust standard errors are estimated to account for two dimensions of cluster correlation (fund and year). This approach allows for correlations among different funds in the same year as well as correlations among different years in the same fund.

	Mutual Funds
β_2 from using MKT in the market-timing estimation	–0.037 (–0.61)
β_2 from using UNC in the macro-timing estimation	0.609 (1.62)