Managerial Talent and Hedge Fund Performance*

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

ABSTRACT

We propose a new measure of managerial skill based on the maximum monthly returns of hedge funds over a fixed time interval and test if this new measure (*pMAX*) is an indicator of greater managerial talent leading to superior fund performance. We find significant cross-sectional variations and persistence in *pMAX*. Our main finding indicates that hedge funds in the highest *pMAX* quintile generate 8.4% more annual returns compared to funds in the lowest *pMAX* quintile. After controlling for a large set of fund characteristics, risk factors, and past performance measures, the positive relation between *pMAX* and future returns remains highly significant. We also show that the directional and semi-directional hedge fund managers can predict and exploit changes in the market and economic conditions by increasing (decreasing) fund exposures to risk factors when market risk and/or economic uncertainty is high (low). However, mutual funds do not have market- or macro-timing ability. Thus, we find no evidence of a significant link between managerial talent of mutual fund managers and their future returns. Overall, the results indicate that the predictive power of *pMAX* over future returns for hedge funds is driven by superior timing ability and better managerial skills of hedge funds.

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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: tgb27@georgetown.edu.
[b] David S. Loeb Professor of Finance, Stern School of Business, New York University, New York, NY, 10012, and Professorial Fellow, University of Melbourne, E-mail: sbrown@stern.nyu.edu.
[c] Associate Professor of Finance, Faculty of Business, Özyegin University, Istanbul, TURKEY. Phone: +90 (216) 564-9518, E-mail: mustafa.caglayan@ozyegin.edu.tr

1. Introduction

Having experienced significant growth over the past two decades, the hedge fund industry plays an important role in investment decisions of a wide variety of investors. As the hedge fund industry grows, there is increasing interest in developing criteria for selecting talented hedge fund managers. Recent studies provide evidence for the presence of professional fund managers in the marketplace that can provide value above and beyond a passively managed fund. However, proponents of passive money management believe the active management industry provides no value-added, because fund managers lack investment-picking skills. This constituency believes markets are efficient; superior performance of hedge funds is attributed to pure randomness (luck), whereas funds that underperform are considered unlucky. However, if we assume markets are perfectly efficient and active managers lack skill, we must simultaneously assume that institutional and (wealthy) individual investors investing in active hegde funds are completely irrational. Despite little evidence of timing ability previously documented for mutual funds, we show that the hedge fund industry with dynamic trading strategies does possess strong market- and macro-timing ability. Hence, we believe both the efficient market and the completely irrational investor hypotheses are farfetched.

Managerial skills are what the manager uses to assist the fund in accomplishing its goals. Specifically, a fund manager will make use of his or her own abilities, knowledge base, experiences, and perspectives to increase the productivity of those with whom they manage. In order to perform their job effectively, fund managers need strong technical, human, and conceptual skills. In this paper, we argue that the value of a talented hedge fund manager is driven by the private, unique information she brings to the investment process. Only unique investment ideas with dynamic trading strategies are likely to generate superior performance because any potential abnormal return resulting from a well-known, heavily traded strategy is likely to be arbitraged away. Therefore, identifying professional fund managers with strong managerial skills and unique investment ideas is crucial for hedge fund investors who pay high fees for superior performance.

If one thinks of hedge fund managers as skilled professionals whose job involves gathering and analyzing data, it seems reasonable to hypothesize that some fund managers may perform better than others. Hedge fund managers have a range of strategies and instruments that are unavailable to mutual fund managers as they seek performance. As Goetzmann, Ingersoll, Spiegel and Welch (2007) observe managers without skill can achieve elevated performance measures using derivative instruments and dynamic trading strategies at the expense of tail risk exposure. They and others propose various alternative performance measures that correct for this issue. However, with only a limited number of returns it is difficult to obtain a reliable estimate of performance in this context. We propose a simple and robust measure of managerial skill based on the maximum monthly returns of hedge funds over a fixed time interval to be used in conjunction with standard performance measures and test if this new measure is an indicator of greater managerial talent leading to superior fund performance in the future.

We investigate whether the extremely large positive returns observed over the past six to 24 months predict future performance of individual hedge funds. First, we conduct univariate portfolio-level analysis.

For each month from January 1995 to December 2014, we form quintile portfolios by sorting individual hedge funds based on their maximum monthly return (*pMAX*) over a specified period, where quintile 1 contains the hedge funds with the lowest *pMAX* and quintile 5 contains the hedge funds with the highest *pMAX*. For the *pMAX* generated over the past 12 months, we find that the average return difference between quintiles 5 and 1 is 0.70% per month and highly statistically significant, indicating that hedge funds in the highest *pMAX* quintile (funds with strong managerial skill) generate 8.4% more annual returns compared to funds in the lowest *pMAX* quintile (funds with weak managerial skill). After controlling for Fama-French-Carhart's four factors of market, size, book-to-market, and momentum as well as Fung-Hsieh's five trend-following factors on currency, bond, commodity, short-term interest rate, and stock index, the return spread between the *high-pMAX* and *low-pMAX* funds (9-factor alpha) remains positive, 0.47% per month, and highly significant.

Next, we provide results from the bivariate portfolios of *pMAX* and competing proxies of managerial skill. Specifically, after controlling for the past 12-month average return, standard deviation, Sharpe ratio, appraisal ratio, incentive fee, and net fund flows in bivariate sorts, *pMAX* remains a significant predictor of future fund returns. The univariate and bivariate portfolio-level analyses clearly indicate that managerial skill is an important determinant of future fund performance and *pMAX* is a distinct, persistent measure of managerial talent containing orthogonal information to alternative measures such as the Sharpe ratio, appraisal ratio, incentive fee, and fund flows.

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 returns, standard deviation, Sharpe ratio, appraisal ratio, and a large set of fund characteristics (age, size, management fee, incentive fee, redemption period, minimum investment amount, lockup and leverage structures). Even after controlling for this large set of fund characteristics, past performance, and alternative measures of managerial skill simultaneously, the significantly positive link between *pMAX* and future fund returns remains highly significant in multivariate Fama-MacBeth regressions. We also perform subsample analyses and find that these regression results are robust across different sample periods and different 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 *pMAX* and future hedge fund returns.

Hedge funds have various trading strategies; some willingly take direct market exposure and risk (directional strategies), while 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 *pMAX* changes among different hedge fund investment styles. The results indicate that the predictive power of *pMAX* gradually increases as we move from the least directional strategies to the most directional strategies. We obtain the highest predictive power of *pMAX* for the directional strategies because the directional funds with higher *pMAX* and stronger managerial skill employ a wide variety of dynamic trading strategies and make extensive use of derivatives, short-selling, and leverage, compared to the non-directional funds with lower *pMAX* and weaker managerial skill.

We also investigate whether hedge funds have the ability to time fluctuations in the equity market and macroeconomic fundamentals. Henriksson-Merton (1981) pooled panel regression results show that the directional funds are 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 frequently using derivatives/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 indicating a stronger link between *pMAX* and future returns for the directional funds with stronger managerial skill can be attributed to the evidence of superior market- and macro-timing ability of these directional hedge fund managers.

We provide an alternative explanation for the superior performance of the directional and semi-directional hedge funds by replicating our main analyses for the mutual fund industry. We first investigate whether managerial skill of mutual fund managers (proxied by the maximum monthly return of mutual funds over the past one year) predicts their future returns. Then, we analyze whether mutual funds have the ability to time fluctuations in the equity market and macroeconomic uncertainty. 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), the results provide no evidence for a significant link between managerial talent of mutual fund managers and their future returns. We also show that while the directional and semi-directional hedge fund managers have the ability to time changes in the market and macroeconomic fundamentals by increasing (decreasing) fund exposure to risk factors when market risk and/or economic uncertainty is high (low), mutual funds, as in the case of the non-directional hedge funds, do not have significant market- or macro-timing ability.

Finally, we examine whether investors take differences in managerial skill into account and show that the ability of *high-pMAX* funds to produce higher returns motivates those hedge fund managers to charge higher management and incentive fees to their clients, compared to the *low-pMAX* funds with weak managerial skill. In addition, we find that the *high-pMAX* funds are able to attract larger capital inflows as well. These two results suggest investors' preference for the *high-pMAX* funds. That is, funds with *high-pMAX* are rewarded with higher fees and also their flows, as a percentage of assets, are significantly greater. This is most probably due to the fact that investors learn about managerial skills and they are indeed willing to pay higher fees and invest more in the *high-pMAX* funds under the expectation of receiving large positive returns in the future.

This paper proceeds as follows. Section 2 provides a literature review. Section 3 describes the data and variables. Section 4 presents the empirical results and provides a battery of robustness checks. Section 5 examines the predictive power of managerial skill for directional, semi-directional, and non-directional hedge funds and sets forth market- and macro-timing tests. Section 6 compares and contrasts hedge funds with mutual funds to provide an alternative way to explain superior performance of directional hedge funds with stronger managerial skill. Section 7 concludes the paper.

2. Literature Review

The concept of sophisticated investors has been widely investigated in empirical asset pricing and corporate finance literatures. Whether such investors with strong manageral skills exist and whether they outperform others has been the subject of debate for at least a few decades, particularly in the literature on mutual funds.[1] While a vast number of performance measures has been proposed and extensively used to identify successful mutual fund managers, several studies question whether these measures actually capture managerial skills, given existing alternative explanations, such as luck (e.g., Kosowski et al. (2006)), model misspecification (e.g., Pastor and Stambaugh (2002), Avramov and Wermers (2006)), survivorship bias (e.g., Brown, Goetzmann, Ibbotson, and Ross (1992) and Brown and Goetzmann (1995)), or weak statistical power of empirical tests undermining the source of high performance (e.g., Kothari and Warner (2001)). Different from the aforementioned literature on mutual funds, our objective is to measure the strength of managerial skill for individual hedge funds and then test whether superior hedge fund performance is related to talent of hedge fund managers.

This paper contributes to the growing literature on the cross-sectional determinants and predictors of hedge fund performance.[2] Bali, Brown, and Caglayan (2011) find a positive (negative) and significant link between default premium beta (inflation beta) and future hedge fund returns. Funds in the highest default premium beta quintile generate 5.8% higher annual returns compared to funds in the lowest default premium beta quintile. Similarly, the annual average return of funds in the lowest inflation beta quintile is 5% higher than the annual average return of funds in the highest inflation beta quintile. Titman and Tiu (2011) find that better-informed hedge funds choose to have less exposure to factor risk. Consistent with their argument, they find that hedge funds that exhibit lower R-squareds with respect to systematic factors have higher Sharpe ratios, higher information ratios, and higher alphas. Sun, Wang, and Zheng (2012) construct a measure of the distinctiveness of a fund's investment strategy (*SDI*) and find that higher *SDI* is associated with better subsequent performance of hedge funds. Bali, Brown, and Caglayan (2012) introduce a comprehensive measure of systematic risk for individual hedge funds by breaking up total risk into systematic and residual risk components. They find that systematic variance is a highly significant factor in explaining the dispersion of cross-sectional returns, while at the same time measures of residual risk and tail risk have little explanatory power. Cao, Chen, Liang, and Lo (2013) investigate how hedge funds manage their liquidity risk by responding to aggregate liquidity shocks. Their results indicate that

[1] See Fama and French (2010) and the references therein.
[2] A partial list includes Fung and Hsieh (1997, 2000, 2001, 2004), Ackermann, McEnally, and Ravenscraft (1999), Liang (1999, 2001), Mitchell and Pulvino (2001), Agarwal and Naik (2000, 2004), Kosowski, Naik, and Teo (2007), Bali, Gokcan, and Liang (2007), Fung et al. (2008), Patton (2009), Jagannathan, Malakhov, and Novikov (2010), Aggarwal and Jorion (2010), Brown, Gregoriou, and Pascalau (2012), Patton and Ramadorai (2013), Agarwal, Arisoy, and Naik (2015), and Agarwal, Ruenzi, and Weigert (2015).

hedge fund managers have the ability to time liquidity by increasing portfolio market exposure when equity market liquidity is high.

This study is also related to an extensive literature on market-timing ability of mutual funds. Following the pioneering work of Treynor and Mazuy (1966), a large number of studies investigated timing ability of professional fund managers. With a few exceptions, most of the earlier work focused on the mutual fund sample and find little evidence of market-timing ability.[3] 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.[4]

One of the challenges facing performance measurement in the hedge fund context is that as Jagannathan and Korajczyk (1986) show, with access to derivative instruments and dynamic portfolio strategies, hedge funds can construct portfolios that show artificial timing ability when no true timing ability exists. This can be accomplished through 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 Treynor and Mazuy sense) and elevated *pMAX* relative to the benchmark, but 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), the manager can attain a Sharpe ratio in excess of the benchmark and a positive alpha.[5] However, an attribute of such concave to benchmark payoff strategies is that the *pMAX* will be less than or equal to that of the benchmark. This hedge fund context suggests that *pMAX* is complementary to traditional performance measures. True managerial skill will be manifest in *both* elevated performance measures *and* high *pMAX* relative to benchmark.[6]

When we use the term *pMAX* in this paper, we inevitably draw a reference to Bali, Cakici, and Whitelaw (2011) and Bali, Brown, Murray, and Tang (2015). However, the term MAX used by Bali et al. (2011, 2015) is to identify demand for lottery-like stocks, whereas in this paper it is used as a proxy for managerial talent leading to superior fund performance.[7] More importantly, in this paper, we investigate the in-sample *pMAX* of hedge funds' managed portfolios, whereas Bali et al. (2011, 2015) examine the

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[3] A partial list includes Henriksson and Merton (1981), Chang and Lewellen (1984), Henriksson (1984), Admati, Bhattacharya, Pfleiderer, and Ross (1986), Jagannathan and Korajczyk (1986), Lehmann and Modest (1987), Ferson and Schadt (1996), Goetzmann, Ingersoll, and Ivkovich (2000), Bollen and Busse (2001), and Jiang, Yao, and Yu (2007).

[4] Chen and Liang (2007), Cao, Chen, Liang, and Lo (2013), and Bali, Brown, and Caglayan (2014).

[5] Strictly speaking, this result requires the benchmark to be distributed as lognormal. 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 benchmark.

[6] Other authors have suggested ways of resolving the ambiguity that arises when *pMAX* and other performance metrics are opposed. 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). The challenge is to obtain reliable measures of performance based on as few as 24 months of hedge fund returns, particularly when these metrics will diverge most from standard measures when benchmark returns take on extreme values.

[7] Also note that MAX for individual stocks is defined as the maximum daily return over the past one month, whereas *pMAX* for hedge funds' managed portfolios is defined as the maximum monthly return over the past six to 24 months.

MAX of portfolios chosen by reference to the prior MAX of their constituent assets. Specifically, we explore the cross-sectional link between managerial talent and timing ability, and their impacts on future returns of hegde funds and mutual funds. Hence, the paper makes a significant contribution to the aforementioned comprehensive literatures on managerial skill, market-timing, and the cross-sectional determinants of fund performance.

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 risk-adjusted returns (alphas) of *pMAX*-sorted portfolios.

3.1. Hedge fund database

This study uses monthly hedge fund data from the Lipper TASS (Trading Advisor Selection System) database. In the database, originally we have information on a total of 19,746 defunct and live hedge funds. However, among these 19,746 funds, there are many funds that are listed multiple times as these funds report returns in different currencies, such as USD, Euro, Sterling, and Swiss Franc. These funds are essentially not separate funds, but just one fund with returns reported on a currency converted basis. In addition, typically a hedge fund has an off-shore fund and an on-shore fund, following the exact same strategy. Therefore, naturally, for all these funds their returns are highly correlated. However, the TASS database assigns a separate fund reference number to each on-shore and off-shore fund, and to each of the funds reporting in different currencies, treating these funds as separate individual funds. In order to distinguish between different share classes (of the same fund) and other actual funds, and not to use any duplicated funds (and hence returns) in our analyses, we first omit all non-USD-based hedge funds from our sample. That is, we keep in our database only the hedge funds reporting their returns in USD. Next, if a hedge fund has both an off-shore fund and an on-shore 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 removing all non-USD-based hedge funds and hedge funds with multiple share classes, our database contains information on a total of 11,099 distinct, non-duplicated hedge funds for the period January 1994 – December 2014, where 8,684 of them are defunct funds and the remaining 2,415 of them are live funds.

The TASS database, in addition to reporting monthly returns (net of fees) and monthly assets under management, also provides information on certain fund characteristics, including management fees, incentive fees, redemption periods, minimum investment amounts, and lockup and leverage provisions.

Table 1 provides summary statistics on hedge fund numbers, returns, assets under management (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 $ billion), 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–December 2014.

Table 1, Panel A reports a sharp reversal in the growth of hedge funds both in numbers and in 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 with 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 1 reports the cross-sectional mean, median, standard deviation, minimum, and maximum values for certain hedge fund characteristics for the period January 1994–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 seen 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 there are a few hedge funds with very large AUM in our database, which reflects true hedge fund industry conditions.

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–December 2014, we do have 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.[8] However, the fact that we use the returns of defunct funds in our analyses as well, removes any potential concerns about the effect of survivorship bias on our main findings.

Another important data bias in a hedge fund study is called the back-fill bias. Once a hedge fund is included into a database, that fund's previous returns are automatically added to that database as well (this process is called "back-filling"). This practice 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 may generate an upward bias in returns of newly reporting hedge funds during their early histories. Fung and Hsieh (2000) report that the median backfill period is about 12 months based on the TASS database from 1994 to 1998. They adjust for this bias by dropping the first 12 months of returns of all individual hedge funds in their sample and report a back-fill bias estimate of 1.4% per annum (see also Malkiel and Saha (2005) and Kosowski, Naik, and Teo (2007) for previous literature on back-fill bias and how they adjust their samples to mitigate the impact of back-fill bias on their results). In order to eliminate the potential effects of back-fill bias on our main findings, in this study we eliminate the returns of all individual hedge funds prior to the date they are added to the database. In other words, in our analyses we use the returns of hedge funds only after they are added to the TASS database.[9] During our sample period January 1994–December 2014, we measure the magnitude of the back-fill bias as 3.66% per annum, calculated as the annual average return difference between the back-fill corrected sample and the back-fill not corrected sample.

The last possible data bias in a hedge fund study is called the multi-period 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, inclusion of hedge funds with shorter return histories than 24 months would be misleading to those investors who seek past performance data to make future investment decisions. Also, a minimum 24-month return history requirement makes sense from a statistical perspective to be able to run regressions and get sensible estimates of alphas, betas, sharpe ratios, and appraisal ratios for individual hedge funds in the sample. Therefore, we require that all hedge funds in the sample to have at least 24 months of return history in our study. 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 less than 24 months). There is a slight chance that we might introduce a new survivorship bias into the system due to deletion of these 2,432 hedge funds from the sample (funds that had return histories 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

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[8] 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%.
[9] In the TASS database, there are 657 hedge funds for which their entry date to the database is unknown. We remove these 657 hedge funds from our sample; as a result the total sample size is reduced to 10,442 funds from 11,099 funds.

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 is a small insignificant percentage difference between the two samples in terms of survivorship bias considerations.[10]

3.2. Variable definitions

In the literature, managerial skill of hedge funds has been proxied by traditional measures of performance such as the CAPM alpha, the Sharpe ratio and the appraisal ratio. In addition to these risk-adjusted return measures, incentive fee and fund flows can be viewed as alternative proxies for managerial skill. This paper introduces a new measure of managerial talent based on the maximum monthly returns of funds over a fixed time interval and examines if the new measure can be considered a sign of successful fund managers leading to superior performance.

pMAX: We use five alternative measures of extreme hedge fund returns (*pMAX*) to proxy for managerial skill. *pMAX6*, *pMAX9*, *pMAX12*, *pMAX18*, and *pMAX24* represent the maximum monthly hedge fund returns over the past 6, 9, 12, 18, and 24 months, respectively.

Control Variables: We use a large set of fund characteristics, past return, volatility, and risk-adjusted return measures to test whether the predictive power of *pMAX* is driven by these variables. Specifically, we use *Size* measured as monthly assets under management in billions of dollars; *Age* measured as the number of months in existence since inception; *Flow* 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;[11] *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 assets under management, typically ranging from 1% to 2%; *MinInvest* measured as 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* 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 (1 if the fund requires investors not able to withdraw initial investments for a pre-specified term, usually 12 months, 0 otherwise); and *DLever* measured as the dummy variable for leverage (1 if the fund uses leverage, 0 otherwise).

In addition to these large set of fund characteristics, in our analyses, we also control for alternative 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 12-month Sharpe ratio (*SR*) computed as the past 12-month average excess return divided by the past 12-month standard deviation, and the appraisal

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[10] This figure is similar to the 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%.

[11] Fund flow is defined as $\{Assets_t – [(1+Return_t) \cdot Assets_{t-1}]\} / Assets_{t-1}$.

ratio (*AR*) obtained from the 9-factor model of Fama-French (1993), Carhart (1997), and Fung and Hsieh (2001):

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\begin{aligned}
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}
\end{aligned}
\tag{1}
$$

where MKT_t, SMB_t, HML_t, and MOM_t are the four factors of Fama-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 by $\sigma_{\varepsilon,i}$. 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: $AR_i = \alpha_i / \sigma_{\varepsilon,i}$.[12]

3.3. Risk factors

We rely on the widely-accepted nine factors when computing the risk-adjusted return of *pMAX*-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 five trend-following factors of Fung and Hsieh (2001) on currency, bond, commodity, short-term interest rate, and stock index. The market factor (MKT) of Fama-French is the value-weighted NYSE/AMEX/NASDAQ (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-market factor (HML) of Fama-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-Hsieh (2001) currency trend-following factor (FXTF) is measured as the return of PTFS (Primitive Trend Following Strayegy) Currency Lookback Straddle; bond trend-following factor (BDTF) is measured as the return of PTFS Bond Lookback Straddle; commodity trend-following factor (CMTF) is measured as the return of PTFS Commodity Lookback Straddle; short-term interest rate trend-following factor (IRTF) is measured as the return of PTFS Short Term Interest Rate Lookback Straddle; and stock index trend-following factor (SKTF) is measured as the return of PTFS Stock Index Lookback Straddle.[13]

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[12] By selecting a basket of investments, the managers of an active investment fund attempt to beat the returns of a relevant benchmark or of the overall market. The appraisal ratio measures the managers' performance by comparing the return of their security picks to the specific risk of those selections. The higher the ratio, the better the performance of the manager in question.

[13] The monthly returns on four factors of Fama-French-Carhart are obtained from Kenneth French's online data library: 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, SKTF are provided by David Hsieh at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

4. Empirical Results

In this section, we investigate whether the maximum monthly return of individual hedge funds (*pMAX*) can predict their future performance. We conduct parametric and nonparametric tests to assess the predictive power of *pMAX* over future hedge fund returns. First, we perform univariate portfolio-level analysis. Second, we examine the significance of cross-sectional persistence in *pMAX*. Third, we provide average portfolio characteristics of *pMAX*-sorted portfolios of individual hedge funds. Fourth, we report results from bivariate portfolios of *pMAX* and competing proxies of managerial skill. Fifth, we provide a detailed analysis of the interaction between *pMAX* and standard deviation. Sixth, we compare the relative performance of *pMAX* and the appraisal ratio in predicting future returns. Seventh, we present results from univariate and multivariate cross-sectional regressions controlling for fund characteristics, past return, volatility, and liquidity measures. Eighth, we investigate whether the predictive power of *pMAX* for future fund returns remains intact during subsample periods when significant structural breaks are observed. Finally, we examine the long-term predictive power of *pMAX*.

4.1. Univariate portfolio analysis of pMAX

For each month, from January 1995 to December 2014, we form quintile portfolios by sorting individual hedge funds based on their maximum monthly return over the past 6, 9, 12, 18, and 24 months (*pMAX6*, *pMAX9*, *pMAX12*, *pMAX18*, and *pMAX24*), where quintile 1 contains the hedge funds with the lowest *pMAX* and quintile 5 contains the hedge funds with the highest *pMAX*. Table 2 shows the average *pMAX* values and the next month average returns on *pMAX*-sorted portfolios. The last two rows in Table 2 display the differences between quintile 5 and quintile 1 the average monthly returns and the 9-factor alphas.

The top panel in Table 2 presents the average magnitude of *pMAX6*, *pMAX9*, *pMAX12*, *pMAX18*, and *pMAX24* for the *pMAX*-sorted portfolios. As expected, the maximum monthly return of hedge funds increases as the estimation window increases from 6 to 24 months. The first column in Table 2 shows that, for *pMAX6*-sorted portfolios, the average maximum return of hedge funds over the past 6 months is 1.07% per month for quintile 1 and 12.67% per month for quintile 5. Comparing the first and last columns of the top panel in Table 2 shows that the corresponding average *pMAX* values are considerably higher for *pMAX24*-sorted portfolios; the average maximum return of hedge funds over the past 2 years is 2.24% per month for quintile 1 and 19.63% per month for quintile 5. Overall, the results in the top panel of Table 2 indicate substantial cross-sectional variations in all measures of *pMAX*.

The bottom panel in Table 2 shows that for each *pMAX* measure, moving from quintile 1 to quintile 5, the next month average return on the *pMAX*-sorted portfolios increases monotonically, leading to an economically and statistically significant return spread between the *high-pMAX* and low- *pMAX* quintiles. Specifically, for *pMAX6*-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 *pMAX* quintile (funds with stronger managerial skill) generate about 9.72% more annual returns compared to funds in the lowest *pMAX* quintile (funds with weaker managerial skill). Similar return spreads are obtained from other measures of *pMAX* as well. The average return difference between quintiles 5 and 1 is 0.75% per month (*t*-stat. = 3.79) for *pMAX9*-sorted portfolios, 0.70% per month (*t*-stat. = 3.48) for *pMAX12*-sorted portfolios, 0.56% per month (*t*-stat. = 3.08) for *pMAX18*-sorted portfolios, and 0.53% per month (*t*-stat. = 2.94) for *pMAX24*-sorted portfolios.

We also check whether the significant return spread between *high-pMAX* and *low-pMAX* funds is explained by Fama-French-Carhart's four factors of market, size, book-to-market, and momentum as well as Fung-Hsieh's five trend-following factors on currency, bond, commodity, short-term interest rate, and stock index. As shown in the last row of Table 2, the 9-factor alpha difference between quintiles 5 and 1 is positive and significant for all measures of *pMAX*. Specifically, the risk-adjusted return spread between quintiles 5 and 1 is 0.55% per month (*t*-stat. = 2.87) for *pMAX6*-sorted portfolios, 0.50% per month (*t*-stat. = 2.70) for *pMAX9*-sorted portfolios, 0.47% per month (*t*-stat. = 2.44) for *pMAX12*-sorted portfolios, 0.37% per month (*t*-stat. = 1.99) for *pMAX18*-sorted portfolios, and 0.34% per month (*t*-stat. = 1.80) for *pMAX24*-sorted portfolios. These results suggest that after controlling for the well-known factors, the return spread between *high-pMAX* and *low-pMAX* funds remains positive and significant.[14]

Next, we investigate the source of the raw and risk-adjusted return difference between the *high-pMAX* and *low-pMAX* portfolios: Is it due to outperformance by *high-pMAX* funds, underperformance by *low-pMAX* funds, or both? For this, we compare the economic and statistical significance of the average returns and the 9-factor alphas of quintile 1 vs. quintile 5. Panel A of Table 3 shows for *pMAX12*-sorted portfolios that the average return and the 9-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-pMAX* funds are economically and statistically insignificant. On the other hand, the average return and the 9-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-pMAX* funds. These results provide evidence that the positive and significant return spread between the *high-pMAX* and *low-pMAX* funds is due to outperformance by the *high-pMAX* funds with stronger managerial skill, but not due to underperformance by the *low-pMAX* funds.[15]

In addition to the average raw returns and alphas, we compute the annualized Sharpe ratios and the 9-factor appraisal ratios of quintiles 1 and 5.[16] The annualized Sharpe ratio is found to be 0.33 for the *low-*

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[14] As expected, the predictive power of *pMAX* does not remain significant when it is generated from long estimation windows because the maximum return observed in distant past does not capture future managerial skill that leads to higher future returns. For *pMAX24*-sorted portfolios, the 9-factor alpha spread between quintiles 5 and 1 (0.34% per month) is economically significant, but it is only marginally significant with a *t*-statistic of 1.80. Consistent with our expectations, the predictive power of *pMAX* becomes weaker when we extend the estimation window from 24 to 36 months.

[15] Instead of repeating the full set of analyses for all measures of *pMAX*, we present the rest of our results based on *pMAX12* starting with Table 3 (and onwards). For notational simplicity, the maximum return over the past 12 months is from now on denoted by *pMAX*.

[16] Brown, Goetzmann, Ibbotson, and Ross (1992) provide evidence that a fund that takes substantial risk and wins (thus earning a high *pMAX*), that survives to a second year maintaining the same risk characteristics will either win

pMAX funds (quintile 1) and 0.83 for the *high-pMAX* funds (quintile 5). This indicates that the risk-adjusted return for the *high-pMAX* funds is more than twice as large as that of the *low-pMAX* funds. Similarly, the 9-factor appraisal ratio is estimated to be –0.02 for the *low-pMAX* funds (quintile 1) and 0.21 for the *high-pMAX* funds (quintile 5). This again implies that hedge funds with strong managerial skill generate higher risk-adjusted returns compared to funds with weak managerial skill, as the appraisal ratio measures the quality of a fund's investment-picking ability.

Proponents of passive money management believe that active portfolio managers do not provide significant value-added, because these fund managers lack asset-picking skills. This constituency believes markets are efficient; i.e., funds that outperform are considered lucky, funds that underperform are considered unlucky. However, our results suggest that there are certainly some professional money managers in the marketplace that can provide value above and beyond that can be obtained from a passively managed fund. Having said that, one may still wonder if investing in an index fund is the optimal decision for investors who lack the time and/or skills to identify skilled hedge fund managers. To test this hypothesis, we compute the annualized Sharpe ratio and the 8-factor appraisal ratio of the S&P500 index (passive money management) and then compare its risk-adjusted performance with the corresponding performance measures of the *high-pMAX* and *low-pMAX* funds.[17]

For the sample period of January 1995–December 2014, the annualized Sharpe ratio for the S&P500 index is estimated to be 0.52, which is 58% higher than the annualized Sharpe ratio for the *low-pMAX* funds with weak managerial skill. This result suggests that investing in an index fund could be a better option for those investors who would only invest in hedge funds with weak managerial skill. More importantly, however, the annualized Sharpe ratio for the *high-pMAX* funds is 60% higher than the annualized Sharpe ratio of the S&P 500 index, implying significant rewards for finding successful fund managers with strong investment-picking ability. Similar results are obtained from the 8-factor appraisal ratios as well; 0.07 for the *low-pMAX* funds, 0.16 for the S&P500 index, and 0.27 for the *high-pMAX* funds. Overall, these results provide evidence that active fund managers, by selecting a basket of investments, can indeed beat the overall market on a risk-adjusted return basis.

4.2. Persistence of pMAX

Of course, the maximum return over the past 12 months documented in Panel A of Table 3 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

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or lose big. If these funds with high *pMAX* lose, they may well die and so there could be a preponderance of winners conditioning on survival. Brown et al. (1992) point out a way to correct for this bias using the appraisal ratio rather than alpha. Hence, following Brown et al. (1992), we compute the appraisal ratio of *pMAX*-sorted portfolios to address the look-ahead bias that may result from the necessity of funds surviving both a 12-month estimation period and a subsequent evaluation period.

[17] When computing the 8-factor appraisal ratio for the S&P500 index, we use equation (1) without the market factor (MKT) since the S&P500 index is a proxy for the aggregate stock market and it is highly correlated with the value-weighted CRSP index.

management fees for hedge funds that have exhibited *high-pMAX* in the past in the expectation that this behavior will be repeated in the future. However, a natural question is whether these expectations are rational. Panel B of Table 3 investigates this issue by presenting the average month-to-month portfolio transition matrix. Specifically, Panel B 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 *pMAX* is completely random, then all the probabilities should be approximately 20%, since a *high-pMAX* or *low-pMAX* in one month should say nothing about the *pMAX* 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 putting a 12-month gap between the lagged and lead *pMAX* variables. Of greater importance, this persistence is especially strong for the extreme *pMAX* quintiles. Panel B of Table 3 shows that for the 12-month-ahead persistence of *pMAX*, 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 *pMAX* successfully predicts future *pMAX* and hence the maximum return observed over the past 12 months does capture the strength of future managerial talent leading to superior future performance.

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

$$pMAX_{i,t+12} = \lambda_{0,t} + \lambda_{1,t} \cdot pMAX_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+12}, \qquad (2)$$

where $pMAX_{i,t}$ is the maximum monthly return of fund *i* in month *t* over the past 12 months (from month *t* to *t*–12), $pMAX_{i,t+12}$ is the 12-month-ahead *pMAX* of fund *i* (from month *t* to *t*+12), and $X_{i,t}$ denotes past return, volatility, and other characteristics of fund *i* in month *t*. Specifically, $X_{i,t}$ includes the past 12-month average return (*AVRG*), the past 12-month standard deviation (*STDEV*), the past 1-month return (*LagRet*), and fund characteristics; *Size*, *Age*, *Flow*, *IncentFee*, *MgtFee*, *MinInvest*, *Redemption*, *DLockup*, and *Dlever*.

Table I in the online appendix reports the average cross-sectional coefficients from these regressions and the Newey-West adjusted *t*-statistics. In the univariate regression of 12-month-ahead *pMAX* on current *pMAX*, the average slope coefficient is positive, quite large, and extremely statistically significant, and the average R-squared 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. This fund-level cross-sectional regression result confirms our finding from the portfolio-level transition matrix presented in Panel B of Table 3. When the aforementioned 12 control variables are added to the regression, the coefficient on lagged *pMAX* remains large and highly significant (the last row in Table I). Besides *pMAX*, of the remaining 12 variables, it is the standard deviation (*STDEV*), past 12-month average return (*AVRG*), past 1-month return (*Lagret*), and Incentive Fee (*IncentFee*) that contribute most to the preditive power of the regression, with univariate R-squareds of 6.7%, 5.6%, 4.6%, and 3.2%, respectively. The remaining 8 variables all have univariate R-squareds of less than 3%. Overall, the results in Table I indicate that the persistence of *pMAX* is not captured by size, age, fee structure, risk/liquidity attibutes, and other characteristics of individual funds.

4.3. Average portfolio characteristics

To obtain a clearer picture of the composition of the *pMAX*-sorted portfolios, Panel C of Table 3 presents summary statistics for the hedge funds in the quintiles. Specifically, Panel C reports the cross-sectional averages of various characteristics for the funds in each quintile averaged across the months. We report average values for the sort variable (the maximum return over the past 12 months denoted by *pMAX*), the past 12-month return (*AVRG*), the past 12-month standard deviation (*STDEV*), the past 1-month return (*LagRet*), and fund characteristics; *Size*, *Age*, *Flow*, *IncentFee*, *MgtFee*, *MinInvest*, *Redemption*, *DLockup*, and *Dlever*.

Panel C of Table 3 shows that the *high-pMAX* funds with stronger managerial skill have higher average 12-month return, higher 12-month standard deviation, higher past one-month return, higher incentive fee, higher management fee, larger fund flow, lower minimum investment amount, lower redemption period, and they have more frequent use of leverage. However, there is no clear pattern between *pMAX* and fund size, fund age, and lockup. These average portfolio characteristics economicaly make sense because funds with stronger managerial skill (on average) outperform funds with weaker managerial skill. The ability of the *high-pMAX* funds to produce higher returns motivates them to charge higher management and incentive fees to their clients, compared to the *low-pMAX* funds with weak managerial skill. The *high-pMAX* funds also attract more capital. Accodingly, their clients are indeed willing to pay higher fees and invest more in the *high-pMAX* funds under the expectation of getting higher returns in the future. The findings in Panel C of Table 3 also suggest that the *high-pMAX* funds have more frequent use of dynamic trading strategies with derivatives and leverage, which may enable them to possess better market-timing and macro-timing ability.[18] Hence, the monthly returns of the *high-pMAX* funds have higher volatility than those of the *low-pMAX* funds.

These results also indicate that the cross-sectional predictive power of the maximum return over the past 12 months (used as a proxy for managerial skill) can be driven by its correlation with AVRG, STDEV, LagRet, IncentFee, MgmtFee, Flow, MinInvest, Redemption, and/or Dlever. We address this potential concern in the following two sections by providing different ways of dealing with the potential interaction of *pMAX* with the aforementioned fund characteristics and risk factors. Specifically, we test whether the positive relation between *pMAX* and the cross-section of hedge fund returns still holds once we control for these variables using bivariate portfolio sorts and Fama-MacBeth (1973) regressions.

[18] We provide a formal test of this hypothesis in Section 6.

4.4. Bivariate portfolio analysis of pMAX and alternative measures of skill/performance

In this section, we conduct a similar nonparametric portfolio analysis, but this time by accounting for the interaction between *pMAX* and alternative proxies for skill and performance. Basically, we perform a bivariate quintile portfolio test for *pMAX* by controlling for the past 12-month average return (AVRG), the past 12-month standard deviation (STDEV), the past 12-month Sharpe ratio (SR), the apprasisal ratio (9-factor AR) defined in equation (1), incentive fee, and fund flows.

To perform this test, in Table 4 quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds first based on each control variable (i.e., competing proxy for managerial skill; AVRG, STDEV, Sharpe ratio, Appraisal ratio, incentive fee, and fund flows). Then, within each control variable sorted portfolio, hedge funds are further sorted into sub-quintiles based on their *pMAX*. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX* within each control variable sorted quintile portfolio and quintile 5 is the portfolio of hedge funds with the highest *pMAX* within each control variable sorted portfolio. In each column of Table 4, the top panel reports the average *pMAX* in each quintile and the lower panel reports those same quintiles' next month average returns. The last two rows in Table 4 show the monthly average return differences and the 9-factor alpha differences between quintile 5 (*high-pMAX* funds) and quintile 1 (*low-pMAX* funds).

A notable point in Table 4 is that moving from the *low-pMAX* to *high-pMAX* quintile, the next-month average return on *pMAX*-sorted portfolios increases monotonically after controlling for all competing proxies of managerial skill. Specifically, the average return difference between quintiles 5 and 1 is 0.44% per month with a Newey-west *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 past 12-month Sharpe ratio, 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 the fund flows. We also check whether this significant return difference between the *high-pMAX* and *low-pMAX* portfolios from bivariate sorts can be explained by Fama-French (1993) and Carhart's (1997) four factors as well as Fung and Hsieh's (2001) five trend-following factors. As shown in the last row of Table 4, the 9-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 Newey-West *t*-statistics well above 2.00.

These results provide strong evidence that after controlling for competing proxies of managerial skill and a large set of risk factors, the return difference between the *high-pMAX* and *low-pMAX* funds remains positive and highly significant. Hence, we conclude that *pMAX* can be viewed as an indicator of graeter managerial talent leading to superior future performance.

4.5. A detailed analysis of the interaction between pMAX and STDEV

In this section, we start with a detailed analysis of the interaction between *pMAX* and volatility. As shown in Panel C of Table 3, hedge funds with high *pMAX* also have high standard deviation of monthly returns. Thus, one may wonder if *pMAX* is just a proxy for total risk instead of managerial talent. To address this potential concern, in Table II of the online appendix, we conduct 5x5 conditional (sequentially) sorted bivariate portfolio analysis of *pMAX* and STDEV. Specifically, hedge funds are first sorted into quintile portfoios based on STDEV and then, within each STDEV quintile, hedge funds are further sorted into sub-quintiles based on their *pMAX*. The last column in Table II shows that moving from the *low-pMAX* to *high-pMAX* quintile, the next-month average return on *pMAX*-sorted portfolios (averaged across the STDEV quintiles) increases monotonically. After controlling for the standard deviation of monthly returns, the average return and alpha spreads between the *low-pMAX* and *high-pMAX* quintiles are 0.69% and 0.68% per month, respectively, and highy significant with Newey-West *t*-statistics of 5.71 and 5.00. This result (also summarized in Table 4) clearly shows that controlling for STDEV does not affect the significant predictive power of *pMAX* on future fund returns.

Table II also shows that, within all quintiles of STDEV, the average return spreads between the *low-pMAX* and *high-pMAX* 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 *low-pMAX* and *high-pMAX* 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. Another notable point in Table II is that the return and alpha spreads between the *low-pMAX* and *high-pMAX* quintiles are much larger for hedge funds with high volatility compared to those with low volatility. To examine if there is a significant difference between the performance of high-*pMAX*&high-STDEV funds vs. low-*pMAX*&low-STDEV funds, we conduct the difference-in-differences tests on the average return and alpha spreads between the *low-pMAX* and *high-pMAX* quintiles for funds in high-STDEV vs. low-STDEV quintiles. We find that the average return spread between the *low-pMAX* and *high-pMAX* quintiles for funds with high-volatility vs. low-volatility is economically large (0.51% per month = 1.07% – 0.56%) and statistically significant with a *t*-statistic of 2.10. Similarly, the 9-factor alpha difference between the *low-pMAX* and *high-pMAX* quintiles for funds with high-volatility vs. low-volatility is also economically large (0.55% per month = 1.12% – 0.57%) and highly significant with a *t*-statistic of 2.02. Overall, these results indicate that funds with high *pMAX* and high STDEV significantly outperform funds with low *pMAX* and low STDEV. More importantly, controlling for STDEV does not reduce the empirical performance of *pMAX* in predicting future hedge fund returns.

Lastly, to control for the effect of STDEV on *pMAX*, we introduce an alternative measure of managerial talent scaled by the standard deviation of hedge fund returns, *pMAX*/STDEV. For each month, from January 1995 to December 2014, we form quintile portfolios by sorting individual hedge funds based on their *pMAX*/STDEV ratios. Table III of the online appendix presents the average *pMAX/*STDEV ratio in each quintile, the next month average return and the 9-factor alpha for each quintile. Table III shows that, moving from quintile 1 to quintile 5, the next month average return and alpha on the *pMAX/*STDEV sorted portfolios increase monotonically, leading to economically and statistically significant return and alpha spreads between the low-*pMAX/*STDEV and high-*pMAX/*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, and highly significant with Newey-West *t*-statistics of 4.42 and 5.17, respectively. Overall, these results provide evidence that *pMAX* is not a proxy for total risk, instead it is an intuitive and statistically strong proxy for managerial talent even after controlling for volatility.

4.6. Managerial talent versus investment-picking ability: pMAX vs. the appraisal ratio

We now compare the relative performance of managerial talent (proxied by *pMAX*) and invesment-picking ability (proxied by the appraisal ratio) in predicting future returns. Table IV of the online appendix presents 5x5 conditional (sequentially) sorted bivariate portfolio analysis of *pMAX* and the appraisal ratio (AR). Specifically, hedge funds are first sorted into quintile portfoios based on AR and then, within each AR quintile, hedge funds are further sorted into sub-quintiles based on their *pMAX*. Table IV shows that, within all AR quintiles, moving from the *low-pMAX* to *high-pMAX* quintile, the next-month average return on *pMAX*-sorted portfolios increases monotonically. The last column in Table IV shows that, after controlling for the appraisal ratio, the average return and alpha spreads between the *low-pMAX* and *high-pMAX* quintiles are 0.69% and 0.50% per month, respectively, and highy significant with *t*-statistics of 3.46 and 2.60. Moreover, within all quintiles of AR, the average return spreads between the *low-pMAX* and *high-pMAX* quintiles are economically large, ranging from 0.54% to 0.75% per month, and highly significant with *t*-statistics ranging from 2.33 to 3.60. Similarly, with the exception of the 2nd AR quintile, the corresponding alpha spreads between the *low-pMAX* and *high-pMAX* quintiles are also economically large and highly significant within all AR quintiles; in the range of 0.38% to 0.56% per month with *t*-statistics hovering well above 2.00. In sum, these results (also summarized in Table 4) clearly show that controlling for the appraisal ratio does not affect the significant predictive power of *pMAX* on future fund returns.

In addition to the conditional (sequentially) sorted bivariate portfolio analysis of *pMAX* and AR, we conduct an independently (simultaneously) sorted bivariate portfolio analysis as well. For each month from January 1995 to December 2014, we rank hedge funds according to their *pMAX* and the 9-factor appraisal ratio independently at the same time, and based on these rankings, we assign a quintile number (from 1 to 5, 1 being lowest category and 5 being highest category) to each individual hedge fund for each *pMAX* and AR category. 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 *pMAX* and AR measure. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX* (AR) within each AR (*pMAX*) sorted quintile portfolio and Quintile 5 is the portfolio of hedge funds with the highest *pMAX* (AR) within each AR (*pMAX*) sorted quintile portfolio.

Panel A of Table 5 presents results from independently sorted 5x5 bivariate portfolios of *pMAX* and AR. Within all AR quintiles, moving from the *low-pMAX* to *high-pMAX* quintile, the next-month average return on *pMAX*-sorted portfolios increases monotonically. The column "Average" presents the next-month returns of *pMAX* quintile portfolios averaged across the AR quintiles. After controlling for the appraisal ratio, the raw return and alpha spreads between the *low-pMAX* and *high-pMAX* quintiles are economically large, 0.73% and 0.56% per month, and highy statistically significant with *t*-statistics of 3.63 and 2.91, respectively. More importantly, within all AR quintiles, the average return and alpha spreads between the *low-pMAX* and *high-pMAX* quintiles are also positive and highly significant, without any exception (see the last two columns in Panel A of Table 5).

Similar results are obtained for the appraisal ratio controlling for *pMAX*. Panel A of Table 5 shows that, within all *pMAX* quintiles, moving from the *low*-AR to *high*-AR quintile, the next-month average return on AR-sorted portfolios increases monotonically. The row "Average" presents the next-month returns of AR quintile portfolios averaged across the *pMAX* quintiles. After controlling for *pMAX*, the raw return and alpha spreads between the *low*-AR and *high*-AR quintiles are economically large, 0.52% and 0.61% per month, and highy significant with *t*-statistics of 5.76 and 7.02, respectively. In addition, within all *pMAX* quintiles, the average return and alpha spreads between the *low*-AR and *high*-AR quintiles are also positive and highly significant, without any exception (see the last two rows in Panel A of Table 5)..

Finally, in this section, we point out that the alternative measure of managerial talent scaled by the standard deviation of total returns, *pMAX*/STDEV, could be a more appropriate measure to compare with the appraisal ratio; because AR is defined as the alpha divided by the standard deviation of fund-specific returns. Hence, we horse race *pMAX* and alpha both scaled by the volatility of hedge fund returns. Specifically, we compare the predictive power of *pMAX*/STDEV and the appraisal ratio based on the independently sorted bivariate portfolios of *pMAX/*STDEV and AR. Similar to our earlier findings, the last two columns of Panel B of Table 5 shows that the average return and alpha differences between the low-*pMAX/*STDEV and high-*pMAX/*STDEV quintiles are positive and highly significant in all AR quintiles, without any exception. Likewise, as seen in the last two rows of Panel B of Table 5, the average return and alpha spreads between the low-AR and high-AR quintiles are also positive and highly significant in all *pMAX/*STDEV quintiles, except for quintile 2.

These results provide evidence that managerial talent (proxied by *pMAX* or *pMAX/*STDEV) and investment picking-ability (proxied by appraisal ratio) have orthogonal components that significantly predict the cross-sectional variation in hedge fund returns because controlling for one does not reduce the empirical performance of the other in predicting future returns. The appraisal ratio measures the performance of hedge fund managers by comparing the abnormal return of their security picks to the specific risk of those selections. Hence, higher appraisal ratio indicates better investment-picking ability and better performance of the manager in question. As discussed earlier, higher *pMAX* (or higher *pMAX/*STDEV) represents stronger technical and conceptual skills including unique investment ideas and stronger timing ability. Clearly, funds with high-*pMAX* (or high-*pMAX/*STDEV) also have better investment-picking ability. However, the results in Table 5 show that, in addition to their similar features, *pMAX* and the appraisal ratio have some distinct characteristics, and therefore their predictive power is not subsumed by one another.

4.7. Fama-MacBeth cross-sectional regressions

We have so far tested the significance of *pMAX* as a determinant of the cross-section of hedge fund returns at the portfolio level. The portfolio-level analysis has the advantage of being nonparametric in the sense that we do not impose a functional form on the relation between *pMAX* and future returns. The portfolio-level analysis also has two potentially significant disadvantages. First, it throws away a large amount of information in the cross-section via aggregation. Second, it is a difficult setting in which to control for multiple effects simultaneously. Consequently, we now examine the cross-sectional relation between managerial skill and future returns at the individual fund level using Fama and MacBeth (1973) regressions.

We present the time-series averages of the slope coefficients from the regressions of one-month-ahead hedge fund excess returns on the maximum return over the past 12 months (*pMAX*) 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 premiums. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot pMAX_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+1}, \qquad (3)$$

where $R_{i,t+1}$ is the excess return of fund *i* in month *t*+1, $pMAX_{i,t}$ is the maximum monthly return of fund *i* in month *t* over the past 12 months (from month *t* to *t*–12), and $X_{i,t}$ denotes a large set of fund characteristics such as 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 the one-month lagged fund returns (*LagRet*), the past 12-month average return (*AVRG*), the past 12-month standard deviation (*STDEV*), and the past 12-month Sharpe ratio (SR) computed as the past 12-month average excess return divided by the past 12-month standard deviation.[19]

Panel A of Table 6 presents the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions for the full sample period January 1995 – December 2014. The Newey-West adjusted *t*-statistics are given in parentheses. We first investigate the cross-sectional relation between *pMAX* and future fund returns without taking into account fund characteristics, lagged return, lagged volatility, and lagged risk-adjusted return (Sharpe ratio). Consistent with our earlier findings from the

[19] At an earlier stage of the study, we replace the Sharpe ratio with the appraisal ratio and replicate the multivariate regressions. Since the Sharpe and appraisal ratios are highly correlated in the cross-section of individual hedge funds, the regression results from the appraisal ratio turn out to be very similar to those reported in our tables.

univariate portfolio analysis, Regression (1) in Panel A of Table 6 provides evidence for a positive and highly significant relation between *pMAX* and future fund returns. The average slope from the monthly univariate regressions of one-month-ahead returns on *pMAX* alone is 0.042 with a Newey-West *t*-statistic of 3.52.

To determine the economic significance of this average slope coefficient, we use the average values of *pMAX* in the quintile portfolios. Table 3 shows that the difference in *pMAX* values between average funds in the first and fifth quintile 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 *pMAX*, what would be the change in that fund's expected return? The average slope coefficient of 0.042 on *pMAX* in Panel A of Table 6 represents an economically significant 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 *pMAX*. This result is similar to our earlier finding of a 0.70% per month return difference between the *high-pMAX* and *low-pMAX* funds from univariate portfolio analysis reported in Table 3, Panel A.

After confirming a significantly positive link between *pMAX* and future returns in univariate Fama-MacBeth regresions, we now control for all fund characteristics, lagged return, lagged volatility, and lagged risk-adjusted return simultaneously and test if managerial skill of hedge funds remains a strong predictor of future returns. Regression (2) in Panel A of Table 6 shows that the average slope on *pMAX* is 0.030 with a Newey-West *t*-statistic of 3.35, implying that after controlling for a large set of fund characteristics, risk factors, and alternative proxies of managerial skill, the positive relation between *pMAX* and future hedge fund returns remains highly significant.

As expected, the average slope for *pMAX* in Panel B of Table 6 is somewhat smaller (0.030 in Panel B vs. 0.042 in Panel A) after accounting for the large set of control variables. However, the average slope of 0.030 still represents an economically significant increase of 0.43% per month in the average fund's expected return for moving from the first to the fifth quintile of *pMAX*, controlling for everything else.

A notable point in Table 6 is that the average slope coefficients on the control variables are consistent with earlier studies. Regression (2) in Panel A of Table 6 shows that the average slope on the one-month lagged fund returns (LagRet) and the past 12-month average return (AVRG) is positive and highly significant.[20] Consistent with the findings of Bali, Brown, and Caglayan (2012), the average slope on the standard deviation of fund returns (STDEV) is also positive and statistically significant. In addition, in line with the findings of Titman and Tiu (2012), the average slope on the Sharpe ratio is again positive and highly significant. Despite the fact that past return, past volatility, and past risk-adjusted return

[20] A similar result, that there is serial dependence in hedge fund returns is also found by Agarwal and Naik (2000), Getmansky, Lo, and Makarov (2004), Jagannathan, Malakhov, and Novikov (2010), and Bali, Brown, and Caglayan (2011, 2012, 2014). Jegadeesh and Titman (1993, 2001) find momentum in stock returns for 3, 6, 9, and 12-month horizons, although Jegadeesh (1990) and Lehmann (1990) provide strong evidence for the short-term reversal effect in individual stock returns for the one-week to one-month horizon. In addition to accounting for lagged returns in Fama-MacBeth regressions, we control for this phenomenon using the Carhart (1997) momentum factor in portfolio-level analyses.

measures of individual hedge funds are found to be significant predictors, the significantly positive link between *pMAX* and future fund returns remains highly significant, suggesting that *pMAX* is a strong predictor of future hedge fund performance.

Another interesting observation that emerges from Table 6, Panel A 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.[21] As in previous results, however, the significance of incentive fee does not diminish the predictive power of *pMAX* on future hedge fund returns. One last noteworthy point from Table 6, Panel A is that the minimum investment amount, the redemption period, and the dummy for lockup variables, which are used by Aragon (2007) to measure illiquidity of hedge fund portfolios, also have positive and significant average slope coefficients. This suggests that funds that use lockup and other share restrictions which enable them to invest in illiquid assets earn higher returns in succeeding months, an outcome that coincides with the findings in Aragon (2007). However, even the significance of these liquidity variables does not alter or reduce the predictive power of *pMAX* over hedge fund returns.

4.8. Subsample analyses

The cross-sectional predictability results reported in earlier tables are based on the 20-year sample period from January 1995 to December 2014. We now investigate whether the predictive power of *pMAX* for future fund returns remains intact during subsample periods. We conduct subsample anlaysis by dividing the full sample into two and then examining the significance of *pMAX* for the first decade (January 1995 – December 2004) and the second decade (January 2005 – December 2014) separately. In addition to these two subsample periods, we examine the predictive power of *pMAX* during high and low economic activity (i.e., good vs. 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 trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.[22]

We perform subsample analyses based on the Fama-MacBeth cross-sectional regressions. Panel B of Table 6 shows that, for the first half of our sample, the average slope on *pMAX* is positive and highly significant both in univariate and multivariate regressions. The average slope from the monthly univariate

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[21] This suggests that incentive fee has a strong positive explanatory power for future hedge fund returns (i.e., funds that charge higher incentive fees also generate higher future returns), a finding similar to other studies (see Brown, Goetzmann, and Ibbotson (1999), Liang (1999), and Edwards and Caglayan (2001)).
[22] 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.

regressions of one-month-ahead returns on *pMAX* 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, the average slope on *pMAX* remains positive, 0.028 with a t-statistic of 2.12. These two average slopes (0.036 and 0.028) for the period 1995-2004 represent an economically significant increase of 0.60% and 0.47% per month, respectively, in the average fund's expected return for moving from the first to the fifth quintile of *pMAX*.

Panel C of Table 6 shows that the predictive power of *pMAX* is stronger for the second half of our sample. Specifically, the average slope on *pMAX* 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, the average slope on *pMAX* also remains positive and larger at 0.031 with a *t*-statistic of 2.62, compared to our findings from the first decade (reported in Panel B of Table 6). We find that the economic significance of these two average slopes (0.048 and 0.031) for the period 2005-2014 corresponds to 0.56% and 0.36% per month increase, respectively, in the average fund's expected return when moving from the first to the fifth quintile of *pMAX*. The results in Panels B and C of Table 6 indicate that successful hedge fund managers are able to produce superior returns during both subsample periods.

We now present the Fama-MacBeth regression results during the good and bad states of the economy separately. In Panel D of Table 6, 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–December 2014. Panel D shows that, for the good states of the economy (CFNAI > 0), the average slope on *pMAX* 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 *pMAX* alone is 0.051 with a *t*-statistic of 4.09. After controlling for a large set of fund characteristics, past return, volatility, and risk-adjusted returns, the average slope on *pMAX* remains positive, 0.033 with a *t*-statistic of 3.09. These two average slopes (0.051 and 0.033) for the good states of the economy represent an economically significant increase of 0.73% and 0.47% per month, respectively, in the average fund's expected return for moving from the first to the fifth quintile of *pMAX*.

Panel E of Table 6 examines the predictive power of *pMAX* during low economic activity for those months when the CFNAI index is negative. During the bad states of the economy (CFNAI < 0), the average slope on *pMAX* in univariate regressions is again positive and statisitcally significant; 0.033 with a *t*-statistic of 2.21. After controlling for the same set of variables, the average slope on *pMAX* remains significantly positive at 0.026 with a *t*-statistic of 2.34. We find that the economic significance of these two average slopes (0.033 and 0.026) during the bad states of the economy corresponds to 0.46% and 0.37% per month increase, respectively, in the average fund's expected return when moving from the first to the fifth quintile of *pMAX*. Overall, the results in Panels D and E of Table 6 provide evidence that hedge fund managers with a strong set of skills are able to perform better than those with weak managerial skill during both good and bad states of the economy.

Despite large fluctuations observed in risk, return, and managerial characteristics of hedge funds during these four subperiods, Panels B through E of Table 6 provide evidence of a positive and significant relation between *pMAX* and future fund returns for all subsample periods. These results clearly show that with and without controlling for a large set of variables, managerial skill is an important determinant of the cross-sectional dispersion in hedge fund returns for all states of the economy, including expansionary and contractionary periods.[23]

4.9. Long-term predictive power of pMAX

In this section, we investigate the long-term predictive power of *pMAX*. Our empirical analyses have thus far focused on one-month-ahead return predictability. However, from a practical standpoint it would make sense to investigate the predictive power of *pMAX* for longer investment horizons, since some investors and hedge fund portfolio managers may prefer portfolio holding periods or investment horizons longer than one month. We examine the long-term predictive power of *pMAX* based on the univariate quintile portfolios. Table VI of the online appendix reports the next 3-, 6-, 9-, and 12-month average returns for each of the five *pMAX* sorted quintile portfolios. The average return difference between quintiles 5 and 1 is 0.60% per month (*t*-stat. = 3.42) for 3-month ahead predictability, 0.49% per month (*t*-stat. = 3.13) for 6-month ahead predictability, 0.41% per month (*t*-stat. = 2.68) for 9-month ahead predictability, and 0.37% per month (*t*-stat. = 2.47) for 12-month ahead predictability. These results indicate that the positive relation between *pMAX* and future fund returns is not just a one-month affair. Based on the average return spreads, the maximum return over the past 12 months predicts cross-sectional variation in hedge fund returns 12 months into the future.

The last row in Table VI of the online appendix shows that the 9-factor alpha spread between quintiles 5 and 1 is 0.39% per month (*t*-stat. = 2.29) for 3-month ahead predictability, 0.33% per month (*t*-stat. = 2.11) for 6-month ahead predictability, 0.30% per month (*t*-stat. = 2.04) for 9-month ahead predictability, and 0.25% per month (*t*-stat. = 1.60) for 12-month ahead predictability. The 9-factor alpha spreads show that funds with higher *pMAX* (stronger managerial skill) outperform funds with lower *pMAX* (weaker managerial skill) not just for one-month-ahead, but nine months into the future.

5. Managerial Skill and Hedge Fund Performance by Investment Style

In this section, we first classify hedge funds into three groups (directional, semi-directional, and non-directional) and examine, for each investment style, the strength of managerial skill and its link to derivatives use. Then, we test if the predictive power of *pMAX* changes among different hedge fund strategies. Second, we investigate whether hedge funds have the ability to time fluctuations in the equity

[23] We test the predictive power of *pMAX* over future hedge fund returns with two alternative multivariate Fama-MacBeth specifications as well. Table V of the online appendix reports that, both for the full sample period and the subsample periods, the average slope coefficient on *pMAX* is always positive and highly significant with Newey-West *t*-statistics well above 2.00, suggesting that our results are robust to alternative specifications of cross-sectional regressions.

market and macroeconomic fundamentals. Finally, we test whether investors take differences in managerial skill into account and are willing to pay higher fees and invest more in the *high-pMAX* funds.

5.1. Predictive power of pMAX by hedge fund investment style

We now test whether our main findings change if our analysis is applied to homogeneous groups of hedge funds, i.e., hedge fund investment strategies. 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 fund of funds, long-short equity hedge, event-driven, and multi-strategy funds).

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

Given these three broad hedge fund investment strategies, it is not surprising to see varying strength of managerial skill and varying degrees of market/macro-timing ability by different investment strategy groups. Even within the same investment style group, one can observe varying degrees of exposures to different financial and macroeconomic risk factors over time, as hedge fund managers adjust their exposures dynamically in response to changing market conditions.

To understand the strength and variation in managerial skill among different investment strategies, we first analyze average *pMAX*, standard deviation of *pMAX*, and the spread between maximum and minimum values of *pMAX* for these aforementioned three broad categories of hedge fund investment strategies separately. The third row in Table 7 presents the cross-sectional average of individual funds' *pMAX* 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 *pMAX* within each category during the sample period. The fifth row reports the cross-sectional average of the spread between the maximum and minium values of *pMAX* within each category. As can be noticed by reading from left to right in Table 7, the directional funds have noticeably larger *pMAX*, higher standard deviation of *pMAX*, and greater Max–Min spread of *pMAX* compared to non-directional and semi-directional funds. In addition, the non-directional strategies' *pMAX*, standard deviation of *pMAX*, and Max–Min spread of *pMAX* are considerably smaller compared to the other strategies. Lastly, the semi-directional funds have average *pMAX*, standard deviation of *pMAX*, and Max–Min spread of *pMAX* that are very similar to the all hedge fund group. We believe that directional funds' large standard deviation and large Max–Min spread of *pMAX* might be due to superior market-timing ability of these funds' managers. In particular, when the opportunity comes (or predicted by fund managers), directional funds adjust their portfolios in such a way that they can generate large positive returns, causing their *pMAX* to be more volatile and Max–Min spread to be larger.

Although not reported in Table 7, we test whether the average *pMAX* of directional funds is significantly higher than the average *pMAX* of non-directional funds, semi-directional, and all hedge funds in our sample. We find that the difference between the average *pMAX* of directional and non-directional funds is economically very large, 5.56% (9.61% – 4.05%) per month, and highly significant with a Newey-West *t*-statistic of 22.04. Similar results are obtained when we compare the average magnitude of *pMAX* for directional funds vs. semi-directional and all hedge funds. Specifically, the difference between the average *pMAX* of directional and semi-directional funds is again economically large, 3.63% (9.61% – 5.98%) per month with a Newey-West *t*-statistics of 17.62; and the difference between average *pMAX* of directional and all hedge funds is again economically large, 3.05% (9.61% – 6.56%) per month, and again highly significant with Newey-West *t*-statistics of 20.01. Overall, these results indicate that, for directional funds, the average *pMAX* (proxy for managerial skill) is significantly greater than that of non-directional and semi-directional funds.

The last two rows in Table 7 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 7 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 with higher *pMAX* and stronger managerial skill employ a wide variety of dynamic trading strategies and make extensive use of derivatives, short-selling, and leverage, compared to the semi-directional and non-directional funds with lower *pMAX* and weaker managerial skill.

Based on this new set of results on varying strength of managerial skill among hedge fund investment strategies, we expect our main finding — a significantly positive link between *pMAX* and future returns obtained for the overall hedge fund category — to be strongest for the directional funds with higher *pMAX* and stronger managerial skill, and relatively weaker for the non-directional funds with lower *pMAX* and weaker managerial skill. We now investigate the predictive power of *pMAX* over future hedge fund returns for the three aforementioned investment strategies separately, and check whether indeed a larger *pMAX* and dynamic trading strategies with more frequent use of futures and other derivatives are associated with stronger predictive power. We perform this test in Table 8 by forming univariate quintile portfolios of *pMAX* for each investment style separately and by analyzing the next-month return and alpha differences between the *high-pMAX* and *low-pMAX* quintiles.

A notable point in Table 8 is that the average return and 9-factor alpha spreads between the *high-pMAX* and *low-pMAX* quintiles increase monotonically as we move from the non-directional to the directional funds. Specifically, the average return difference between quintiles 5 and 1 is 0.50% per month (*t*-stat. = 3.11) for the non-directional funds, 0.69% per month (*t*-stat. = 3.00) for the semi-directional funds, and 0.88% per month (*t*-stat. = 3.71) for the directional funds. The 9-factor alpha spreads follow a similar pattern among the three investment strategies; 0.30% per month (*t*-stat. = 2.11) for the non-directional funds, 0.40% per month (*t*-stat. = 2.43) for the semi-directional funds, and 0.76% per month (*t*-stat. = 2.71) for the directional funds.

Combining these new sets of results with the results obtained earlier on the strength of managerial skill (proxied by the magnitude of *pMAX*) and the frequency of derivatives use across different investment styles, we observe an economically and statistically stronger relation between *pMAX* and future returns for funds with higher *pMAX* and more frequent use of futures and other derivatives. Another possible explanation for the stronger performance of funds with higher *pMAX* and more frequent use of derivatives could be the market- and macro-timing ability of hedge fund managers. In the next section, we provide a formal test of the market- and macro-timing ability of the directional, semi-directional, and non-directional hedge funds.

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

While the results from the above analysis suggest the existence of a possible market-timing and/or macro-timing ability by fund managers in directional and semi-directional hedge funds, the analysis conducted thus far is not a direct test for market- or macro-timing. In this section, 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 to each of the three broad categories of hedge fund styles separately and determine whether funds' ability to time market and macroeconomic changes is specific to a group of hedge funds.

We investigate market-timing ability of hedge funds using pooled panel regressions based on the Henriksson and Merton model:[24]

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

where $R_{i,t}$ is 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:

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

In equation (4), regression parameters α, β_1, and β_2 are the intercept, the market beta, and the parameter for market-timing ability, respectively. Market timing indicates an increase (decrease) in market exposure

[24] Similar methodology is also used in a different context by Jagannathan and Korajczyk (1986), Chen and Liang (2007), Cao, Chen, Liang, and Lo (2013), and Caglayan and Ulutas (2013).

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 superior market-timing ability of individual hedge funds.

Following Bali, Brown, and Caglayan (2014), we also investigate macro-timing ability of hedge funds using pooled panel regressions based on a modified model of Henriksson and Merton (1981):

$$R_{i,t} = \alpha + \beta_1 \cdot UNC_t + \beta_2 \cdot UNC_t^{high} + \varepsilon_{i,t}\ , \tag{5}$$

where $R_{i,t}$ is excess return of fund *i* in month *t*, UNC_t is the economic uncertainty index of Bali et al. (2014) in month *t*, and UNC_t^{high} is the economic uncertainty index implying macro-timing ability:

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

In equation (5), regression parameters α, β_1, and β_2 are the intercept, the uncertainty beta, and the parameter for macro-timing ability, respectively. In this regression specification, a positive and significant estimate of β_2 implies superior macro-timing ability of individual hedge funds.

Table 9 presents the estimated values of β_2 and the corresponding *t*-statistics from the pooled panel regression specifications in eqs. (4) and (5) for the sample period January 1995–December 2014. Equations (4) and (5) 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 estimation of clustered robust standard errors).

As reported in the first row of Table 9, for market-timing tests, β_2 is estimated to be positive, 0.277, and highly significant with a *t*-statistic of 2.62 for the directional hedge funds. 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 compared to the semi-directional funds. This indicates that directional hedge fund managers have higher capability to time fluctuations in the equity market. Consistent with our expectation, Table 9 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 9, β_2 is estimated to be positive, 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, 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 compared to the semi-directional funds, implying that the directional hedge fund managers have 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, as directional funds willingly take direct exposure to financial and macroeconomic risk factors, relying on their market-timing and macro-timing ability 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 *pMAX* and future returns for the directional funds with stronger managerial skill (proxied by higher *pMAX*), can be attributed to the evidence of superior market- and macro-timing ability of these directional hedge fund managers.

5.3. Do investors prefer high-pMAX funds?

Our results indicate that hedge fund portfolio managers with better managerial skill and better market- and macro-timing ability will employ an investment strategy that generates larger positive returns (*high-pMAX*). Thus, sophisticated investors should consider past *pMAX* as an indicator of managerial talent. To examine whether investors take differences in managerial skill into account, we test if investors are indeed willing to pay higher fees for funds with *high-pMAX*.

As shown in Panel C of Table 3, the average management and incentive fees of individual funds increase monotonically when moving from quintile 1 to 5 in the univariate *pMAX*-sorted portfolios. Specifically, the average management fee increases monotonically from 1.34% for the *low-pMAX* funds to 1.58% for the *high-pMAX* funds. Similarly, the average incentive fee increases monotonically from 12.9% for the *low-pMAX* funds to 17.9% for the *high-pMAX* funds.[25]

In addition to these portfolio-level analysis presenting a strong positive relation between *pMAX* and fees, we run multivariate Fama-MacBeth regressions to check if this strong relation remains intact after controlling for individual fund characteristics, past performance, and risk/liquidity attributes. Table 10 reports the average intercept and slope coefficients from the Fama-MacBeth regressions of management/incentive fees on *pMAX* with and without control variables for the sample period January 1995 – December 2014. The univariate regression results (line (1) in Panel A and Panel B of Table 10) confirm the portfolio-level results presented in Panel C of Table 3. The multivariate regressions reported in line (2) of Panels A and B of Table 10 produce consistently positive and highly significant average slope coefficients on *pMAX*, indicating a strong positive link between *pMAX* and hedge fund fees after controlling for past fund performance and other fund-specific characteristics.

[25] The TASS database rewrites the fees if hedge funds change their management and/or incentive fee structure. The management and incentive fees used in our empirical analyses are as of December 2014. Since fees do not change much during a fund's history, one can assume that they were set at the beginning of the fund's history.

To test the hypothesis that the *high-pMAX* funds also attract more capital flows, we examine the cross-sectional relation between *pMAX* and the one-month-ahead net flows into the fund. Specifically, we sort individual hedge funds into quintile portfolios based on their *pMAX* and then calculate the average one-month-ahead net flows to funds in each quintile. Although not reported in a seperate table 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-pMAX* funds than for the *low-pMAX* funds. The difference between the net monthly flows of *high-pMAX* and *low-pMAX* funds is also highly significant with a Newey-West *t*-statistic of 3.69.

We also run multivariate Fama-MacBeth regressions to check if this strong predictive relation between *pMAX* and fund flows remains intact after controlling for individual fund characteristics, past performance, and risk/liquidity attributes. Panel C of Table 10 presents the average intercept and slope coefficients from the Fama-MacBeth regressions of the one-month-ahead net fund flows on *pMAX* with and without control variables for the sample period January 1995 – December 2014. The significantly positive average slope on *pMAX* from the univariate regressions (average slope coefficient of 0.020 with a *t*-statistics of 2.96) confirm the portfolio-level results discussed earlier. The multivariate regressions reported in Panel C of Table 10 produce a positive and highly significant average slope coefficient on *pMAX* (average slope coefficient of 0.026 with a *t*-statistics of 3.76), indicating a strong positive link between *pMAX* and the one-month-ahead net flows into the fund after controlling for past fund performance and other fund-specific characteristics.

Overall, the results in Section 5 indicate that the *high-pMAX* funds have more frequent use of dynamic trading strategies with derivatives and leverage, which enable them to possess better market- and macro-timing ability. The ability of the *high-pMAX* funds to produce higher returns motivates them to charge higher management and incentive fees to their clients, compared to the *low-pMAX* funds with weak managerial skill. In addition, the *high-pMAX* funds attract more capital (higher net inflows) as well. The findings in Table 10 show that funds with *high-pMAX* are rewarded with higher fees because investors learn about managerial skills and they are indeed willing to pay higher fees and invest more in the *high-pMAX* funds under the expectation of receiving large positive returns in the future.

6. Evidence from Mutual Funds

We think that an alternative way to explain superior performance of the directional and semi-directional hedge funds with higher *pMAX* and stronger managerial skill is to compare and contrast hedge funds with mutual funds. Therefore, in this section, we provide evidence from mutual funds by replicating our main analyses for the mutual fund industry for the sample period January 1995–June 2013.[26] We first

[26] We use monthly returns of individual mutual funds from the CRSP Mutual Fund database. However, most of the mutual funds in the CRSP database 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. As discussed in Section I of the online appendix, we make sure that each mutual fund is represented with a single share class in our database. After removing multiple share classes, 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 VII of the online

investigate whether managerial talent of mutual fund managers (proxied by the maximum monthly return of mutual funds over the past one year) predicts their future returns. We then analyze whether mutual funds have the ability to time fluctuations in the equity market and macroeconomic fundamentals. Finally, we test the economic and statistical significance of timing ability for hedge funds vs. mutual funds.

6.1. Does managerial skill 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%, it is considered a success. On the flip side, hedge funds seek absolute returns, not related to 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) The founder of a hedge fund is the general partner and an investor in the fund. The manager of a mutual fund is seldom the owner and may not be a significant fund investor; and (vi) Hedge funds have lockup periods typically 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 lock-ups or gates.[27]

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 in a more aggressive manner than mutual funds 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 fund managers without skill can achieve the appearance of positive short term performance at the expense of tail risk exposure.

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

appendix provides summary statistics both on numbers and returns of these single-share class, non-duplicated mutual funds.

[27] There are other differences between hedge funds and mutual funds that are not listed here, such as differences in their regulations, asset allocation, and performance disclosure policies.

strategies with unique investment ideas, we do not expect cross-sectional differences in managerial skills of mutual fund managers to explain cross-sectional dispersion in mutual fund returns. In particular we should not expect mutual funds to exhibit cross sectional dispersion in the *pMAX* criterion unrelated to other performance metrics. Along the same lines, we do not expect mutual funds to have significant market- or macro-timing ability either.

To test these conjectures, we first estimate managerial talent of mutual funds using the maximum monthly return over the past 12 months. Then, for each month, from January 1995 to June 2013, we form quintile portfolios by sorting mutual funds based on their *pMAX*, where quintile 1 contains the mutual funds with the lowest *pMAX* and quintile 5 contains the mutual funds with the highest *pMAX*. Panel A of Table 11 shows the average *pMAX* values and the next month average returns on *pMAX*-sorted portfolios of mutual funds. The last two rows display the differences between quintile 5 and quintile 1 the average monthly returns and the 4-factor Fama-French-Carhart alphas.

The second column of Table 11, Panel A, shows that the average return difference between quintiles 5 and 1 is 0.49% per month, but statistically insignificant with a Newey-West *t*-statistic of 1.23. As shown in the last column of Table 11, Panel A, the risk-adjusted return spread turns out to be negative albeit insignificant. Specifically, the 4-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 *pMAX* quintile do not generate economically or statistically higher risk-adjusted returns than mutual funds in the lowest *pMAX* quintile. Overall, the univariate portfolio results in Table 11 provide no evidence for a significant link between *pMAX* and future returns on mutual funds consistent with the view that derivative instruments and dynamic portfolio strategies are not an important determinant of the cross-sectional differences in mutual fund returns.

6.2. Market- and macro-timing ability of mutual funds

To test our second conjecture, we investigate the market- and macro-timing ability of mutual funds with the same Henriksson-Merton (1981) model that we utilize in our earlier analysis for hedge funds. Panel B of Table 11 presents the estimated values of β_2 and the corresponding *t*-statistics for mutual funds. Essentially, equations (4) and (5) are estimated with a pooled panel regression for the sample period January 1995–June 2013, this time using mutual fund excess returns as the dependent variable. The *t*-statistics reported in parenthesis are again estimated using clustered robust standard errors, accounting for two dimensions of cluster correlation (fund and year). Table 11, Panel B shows that for the equity market index, β_2 is statistically insignificant (a coefficient of –0.037 with a *t*-statistic of –0.61) for mutual funds, providing no evidence of market-timing ability for mutual fund managers. Similar results are obtained for the economic uncertainty index; β_2 is again statistically insignificant (a 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 have the ability to actively vary their exposure to market risk and economic uncertainty up or down in a timely fashion according to the macroeconomic conditions and state of the financial markets. As a result, they can generate superior returns, and there exists a positive and stronger link between their managerial talent and future returns. On the other hand, mutual funds do not have market- or macro-timing ability. In line with this finding, there is no evidence of a significant cross-sectional link between *pMAX* and future returns for mutual funds.

6.3. Testing the economic and statistical significance of timing ability

Can professional fund managers predict and exploit changes in the market and macroeconomic conditions? Starting with Treynor and Mazuy (1966), there has been an extensive literature on market-timing ability of mutual funds. Most of the earlier studies provide little evidence of timing ability for mutual funds, and some studies even find negative timing ability (concavity) which can be interpreted as systematically adjusting market exposure in a perverse way.[28]

In this paper, we explore the cross-sectional link between managerial talent, timing ability, and future fund performance. In particular, we have tested whether hedge fund and mutual fund managers can time the market and/or economic uncertainty by strategically adjusting fund exposures based on their forecasts of future market and macroeconomic conditions. If so, how much economic value does timing skill bring to fund investors? In this section, we investigate this issue by testing the economic and statistical significance of market- and macro-timing ability for the directional, semi-directional, and non-directional hedge funds versus mutual funds.

Panel C of Table 11 presents results from testing the significance of average returns and 4-factor alphas for the *high-pMAX* directional, semi-directional, and non-directional hedge funds versus the *high-pMAX* mutual funds. In the first row of Panel C, the average returns and alphas are compared for the *high-pMAX* directional funds (with strong timing ability) vs. the *high-pMAX* mutual funds (with no timing ability). In the second row, the average returns and alphas are compared for the *high-pMAX* semi-directional funds (with semi-strong timing ability) vs. the *high-pMAX* mutual funds (with no timing ability). In the last row, the average returns and alphas are compared for the *high-pMAX* non-directional hedge funds vs. the *high-pMAX* mutual funds (both groups with no timing ability).

The results reported in the first two rows in Panel C of Table 11 clearly show that the predictive power of managerial talent (proxied by *pMAX*) for future fund performance is substantially higher for the directional and semi-directional funds as compared to mutual funds, because the differences between the average returns and alphas for the *high-pMAX* directional and semi-directional funds vs. the *high-pMAX* mutual funds are economically and statistically significant. The last row of Table 11, Panel C, provides evidence that, due to lack of investment-picking skills and lack of timing ability of non-directional hedge fund managers, the predictive power of managerial skill for future fund performance is not robustly,

[28] Bollen and Busse (2001) using daily return data and Jiang, Yao, and Yu (2007) using portfolio holding data provide supporting evidence of timing ability for mutual funds. Their findings suggest that the identification of market-timing ability may be sensitive to data frequency or data type (see Goetzmann, Ingersoll, and Ivkovich (2000)).

significantly greater for the *high-pMAX* non-directional funds, as compared to the *high-pMAX* mutual funds. Overall, the results in Table 11 suggest that market- and macro-timing ability represent managerial skill adding significant economic value to investors of the directional and semi-directional hedge funds.

7. Conclusion

Investors pay a great deal of attention to the technical, human, and conceptual skills of individuals who are managing their money because investors prefer to put money in hedge funds run by talented managers with unique investment ideas and superior investment-picking skills that generate higher risk-adjusted returns. In light of this investor behavior, a natural question to ask is whether some fund managers are indeed better than others. Since hedge funds do not disclose their trading strategies, security holdings, or asset allocation decisions, identifying managerial talent is a difficult task.

We introduce a new measure of managerial skill based on the maximum monthly returns of hedge funds over the past one year and test if this new measure (*pMAX*) adds information regarding managerial talent beyond standard fund performance measures currently in use. We find that this is indeed the case. Specifically, the hedge funds in the highest *pMAX* quintile (with strong managerial skill) generate 8.4% more annual returns compared to funds in the lowest *pMAX* quintile (with weak managerial skill). After controlling for Fama-French-Carhart's four factors of market, size, book-to-market, and momentum as well as Fung-Hsieh's five trend-following factors on currency, bond, commodity, short-term interest rate, and stock index, the 9-factor alpha spread between the *high-pMAX* and *low-pMAX* funds remains positive and highly significant. We also run fund-level cross-sectional regressions to control for fund characteristics and alternative measures of past performance and managerial skill simultaneously. Both Fama-MacBeth regressions and portfolio-level analyses provide strong corroborating evidence for an economically and statistically significant positive relation between *pMAX* and future returns.

Once we establish our main finding that managerial talent matters for hedge fund performance, we test if the predictive power of *pMAX* gradually increases as we move from the least directional strategies to the most directional strategies. Consistent with our expectation, the predictive power of *pMAX* turns out to be the highest for the directional funds because these funds with higher *pMAX* and stronger managerial skill employ a wide variety of dynamic trading strategies and make extensive use of derivatives, short-selling, and leverage that otherwise obscure standard performance measures. As expected, the predictive power of *pMAX* is found to be the lowest for the non-directional funds with lower *pMAX* and weaker managerial skill. We also investigate whether hedge funds and mutual funds have the ability to time fluctuations in the equity market and macroeconomic fundamentals. The results indicate that the directional hedge fund managers can predict and exploit changes in the market and macroeconomic conditions by increasing (decreasing) fund exposure to risk factors when market risk and/or economic uncertainty is high (low). However, mutual funds do not have market- or macro-timing ability. Thus, we find no evidence of a significant link between managerial talent of mutual fund managers and their future returns.

These results are consistent with our managerial skill hypothesis—skilled hedge fund managers with superior market- and macro-timing ability are more likely to pursue unique investment strategies that result in superior performance, while less-skilled non-directional and mutual fund managers do not have good investiment-picking skills and they are more likely to trade on known strategies. Overall, our findings suggest that *pMAX* is a useful indicator of managerial talent which can be effectively used by investors when selecting individual hedge funds.

Finally, we examine whether hedge fund investors take differences in managerial skill into account. For *high-pMAX* funds, both the management and performance fees are considerably higher compared to other funds. Thus, for investors, the reward for finding talented fund managers is justified with the increased fees that these fund managers charge investors. In sum, our results suggest investors' preference for *high-pMAX* funds; funds with *high-pMAX* are rewarded with higher fees and, also their flows, as a percentage of assets, are significantly greater. This is due to the fact that investors learn about managerial skills and they are indeed willing to pay higher fees and invest more in the *high-pMAX* funds under the expectation of receiving large positive returns in the future.

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Table 1. Descriptive Statistics of Hedge Funds

There are total of 11,099 hedge funds that reported monthly returns to TASS for the years between 1994 and 2014 in this database, of which 8,684 are defunct funds and 2,415 are live funds. For each year from 1994 to 2014, 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 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 1 (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

Table 2. Univariate Portfolios of Alternative *pMAX* measures

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their alternative *pMAX* measures. *pMAX6*, *pMAX9*, *pMAX12*, *pMAX18*, and *pMAX24* 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 *pMAX* measures, and quintile 5 is the portfolio of hedge funds with the highest *pMAX* measures. In each column, the top panel reports the average *pMAX* 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 *pMAX* funds) and quintile 1 (low *pMAX* 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 *pMAX6*	Average Size of *pMAX9*	Average Size of *pMAX12*	Average Size of *pMAX18*	Average Size of *pMAX24*
Q1	1.07	1.45	1.67	1.99	2.24
Q2	2.20	2.69	3.04	3.59	4.02
Q3	3.46	4.17	4.69	5.50	6.11
Q4	5.58	6.61	7.39	8.56	9.49
Q5	12.67	14.51	15.88	17.98	19.63
	Next-month returns of *pMAX6* Quintiles	Next-month returns of *pMAX9* Quintiles	Next-month returns of *pMAX12* Quintiles	Next-month returns of *pMAX18* Quintiles	Next-month returns of *pMAX24* Quintiles
Q1	0.10	0.08	0.09	0.12	0.16
Q2	0.30	0.33	0.33	0.35	0.34
Q3	0.43	0.44	0.45	0.45	0.42
Q4	0.59	0.60	0.58	0.56	0.51
Q5	0.91	0.83	0.79	0.69	0.69
Q5 – Q1 Return Diff.	**0.81** **(3.85)**	**0.75** **(3.79)**	**0.70** **(3.48)**	**0.56** **(3.08)**	**0.53** **(2.94)**
Q5 – Q1 9-factor Alpha Diff.	**0.55** **(2.87)**	**0.50** **(2.70)**	**0.47** **(2.44)**	**0.37** **(1.99)**	**0.34** **(1.80)**

Table 3. Univariate Portfolios of Hedge Funds Sorted by *pMAX*

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

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *pMAX*. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX*, and quintile 5 is the portfolio of hedge funds with the highest *pMAX*. The table reports average *pMAX* 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 *pMAX* and Low *pMAX* 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 *pMAX* 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 3 (continued)

Panel B. 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 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 *pMAX* is completely random, then all the probabilities should be approximately 20%, since a *high-pMAX* or *low-pMAX* in one month should say nothing about the *pMAX* in the following 12 months. Instead, all the 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 *pMAX* variables. The sample period is January 1995–December 2014.

	Low *pMAX*	Q2	Q3	Q4	High *pMAX*	Total
Low *pMAX*	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 *pMAX*	1.6%	4.1%	10.0%	26.1%	58.2%	100.0%

Table 3 (continued)

Panel C. Average Fund Characteristics of *pMAX* Quintile Portfolios

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *pMAX* measure. *pMAX* is the maximum monthly hedge fund returns over the last 12 months. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX* measure, and quintile 5 is the portfolio of hedge funds with the highest *pMAX* measure. This table reports the average fund charactersitics of hedge funds for each of the five quintiles. 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).

	pMAX	AVRG	STDEV	LagRet	Size	Age	Flow	IncentFee	MgtFee	MinInvest	Redemption	DLockup	DLever
Q1	1.67	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	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	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	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	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 4. Bivariate Portfolios of *pMAX* after Controlling for AVRG, STDEV, Sharpe Ratio, 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 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 *pMAX*. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX* within each fund characteristics sorted quintile portfolio (depending on which fund characteristic's effect on *pMAX* is controlled for) and Quintile 5 is the portfolio of hedge funds with the highest *pMAX* within each fund characteristics sorted quintile portfolio (again depending on which fund characteristic's effect on *pMAX* is controlled for). In each column, the top panel reports the average *pMAX* 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 *pMAX* funds) and quintile 1 (low *pMAX* 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.

	pMAX Portfolios after controlling for AVRG	*pMAX* Portfolios after controlling for STDEV	*pMAX* Portfolios after controlling for SR	*pMAX* Portfolios after controlling for 9-Factor AR	*pMAX* Portfolios after controlling for Incentive Fee	*pMAX* Portfolios after controlling for Fund Flows
Q1	2.39	3.42	1.84	1.78	1.76	1.75
Q2	3.74	4.96	3.24	3.13	3.26	3.15
Q3	5.16	6.04	4.85	4.71	4.90	4.78
Q4	7.30	7.38	7.42	7.32	7.38	7.38
Q5	14.06	10.86	15.30	15.47	15.36	15.60
	Next-month returns of *pMAX* Quintiles	Next-month returns of *pMAX* Quintiles	Next-month returns of *pMAX* Quintiles	Next-month returns of *pMAX* Quintiles	Next-month returns of *pMAX* Quintiles	Next-month returns of *pMAX* Quintiles
Q1	0.21	0.06	0.12	0.04	0.10	0.09
Q2	0.37	0.34	0.32	0.29	0.34	0.35
Q3	0.47	0.49	0.45	0.39	0.47	0.45
Q4	0.53	0.61	0.56	0.53	0.55	0.58
Q5	0.65	0.75	0.79	0.73	0.78	0.77
Q5 – Q1 Return Diff.	**0.44** **(3.02)**	**0.69** **(5.71)**	**0.67** **(3.39)**	**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)**	**0.50** **(2.60)**	**0.46** **(2.44)**	**0.45** **(2.47)**

Table 5. Managerial Talent versus Investment-Picking Ability

Panel A. Independent Bivariate Sorts of *pMAX* and the Appraisal Ratio (AR)

This table conducts an independently (simultaneously) sorted bivariate portfolio analysis of *pMAX* and the Appraisal Ratio. For each month from January 1995 to December 2014, we rank hedge funds according to their *pMAX* and the 9-Factor Appraisal Ratio (AR) 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 *pMAX* 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 *pMAX* and AR measure. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX* (AR) within each AR (*pMAX*) sorted quintile portfolio and Quintile 5 is the portfolio of hedge funds with the highest *pMAX* within each AR (*pMAX*) sorted quintile portfolio. The column "Average" presents the next-month returns of *pMAX* quintile portfolios averaged across the AR quintiles. The row "Average" presents the next-month returns of AR quintile portfolios averaged across the *pMAX* quintiles. The last two columns show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*pMAX* funds) and quintile 1 (Low-*pMAX* 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 *pMAX* 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.

		pMAX quintiles							
		Q1	Q2	Q3	Q4	Q5	Average	Q5–Q1 Ret Diff.	Q5–Q1 Alpha Diff.
	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)**
AR quintiles	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 5 (continued)

Panel B. Independent Bivariate Sorts of *pMAX/*STDEV and the Appraisal Ratio (AR)

This table conducts an independently (simultaneously) sorted bivariate portfolio analysis of *pMAX/*STDEV and the Appraisal Ratio. For each month from January 1995 to December 2014, we rank hedge funds according to their *pMAX/*STDEV ratios and the 9-Factor Appraisal Ratio (AR) 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 *pMAX/*STDEV 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 *pMAX/*STDEV and AR measure. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX/*STDEV (AR) within each AR (*pMAX/*STDEV) sorted quintile portfolio and Quintile 5 is the portfolio of hedge funds with the highest *pMAX/*STDEV within each AR (*pMAX/*STDEV) sorted quintile portfolio. The column "Average" presents the next-month returns of *pMAX/*STDEV quintile portfolios averaged across the AR quintiles. The row "Average" presents the next-month returns of AR quintile portfolios averaged across the *pMAX/*STDEV quintiles. The last two columns show the monthly average return differences and the 9-factor alpha differences between quintile 5 (High-*pMAX/*STDEV funds) and quintile 1 (Low-*pMAX/*STDEV 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 *pMAX/*STDEV 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.

		pMAX/STDEV quintiles							
		Q1	Q2	Q3	Q4	Q5	Average	Q5–Q1 Ret Diff.	Q5–Q1 Alpha Diff.
	Q1	-0.22	0.31	0.25	0.37	0.30	0.20	**0.52 (2.73)**	**0.65 (2.75)**
	Q2	0.01	0.35	0.44	0.38	0.57	0.35	**0.56 (2.99)**	**0.62 (3.09)**
AR quintiles	Q3	0.17	0.43	0.54	0.52	0.62	0.46	**0.45 (2.90)**	**0.42 (2.19)**
	Q4	0.29	0.43	0.56	0.63	0.61	0.50	**0.32 (1.96)**	**0.40 (2.38)**
	Q5	0.26	0.36	0.61	0.70	0.63	0.51	**0.38 (2.86)**	**0.40 (2.77)**
	Average	0.10	0.38	0.48	0.52	0.55		**0.45 (3.31)**	**0.50 (3.45)**
	Q5–Q1 Ret Diff.	**0.48**	0.05	**0.36**	**0.32**	**0.33**	**0.31**		
		(3.28)	(0.43)	**(3.10)**	**(3.36)**	**(2.40)**	**(4.03)**		
	Q5–Q1 Alpha Diff.	**0.58**	0.09	**0.42**	**0.45**	**0.33**	**0.38**		
		(3.26)	(0.61)	**(2.69)**	**(3.73)**	**(1.92)**	**(3.57)**		

Table 6. Fama-MacBeth Cross-sectional Regressions of Hedge Fund Returns on *pMAX* 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 *pMAX* 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 (in Panel A) as well as for two subsample periods (Panels B and C) and for good and bad states of the economy (Panels D and E). 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	*pMAX*	SR	AVRG	STDEV	LagRet	Size	Age	Flow	IncentFee	MgtFee	MinInv	Redemption	DLockup	DLever
Panel A: Full sample period (1995:01 – 2014:12)															
(1)	0.208	**0.042**													
	(2.25)	**(3.52)**													
(2)	0.065	**0.030**	**0.100**	**0.205**	**0.070**	**0.072**	–0.006	–0.003	–0.001	**0.004**	0.013	**0.004**	**0.001**	**0.096**	0.009
	(0.59)	**(3.35)**	**(4.19)**	**(4.82)**	**(1.96)**	**(5.62)**	(–0.19)	(–1.63)	(–1.16)	**(1.91)**	(0.43)	**(3.36)**	**(2.01)**	**(3.04)**	(0.50)
Panel B: First half of the full sample period (1995:01 – 2004:12)															
(1)	0.380	**0.036**													
	(3.57)	**(2.29)**													
(2)	0.166	**0.028**	**0.110**	**0.202**	**0.083**	**0.075**	–0.028	–0.006	–0.001	0.003	0.029	**0.006**	**0.002**	**0.172**	0.013
	(0.84)	**(2.12)**	**(2.50)**	**(3.38)**	**(1.76)**	**(4.19)**	(–0.42)	(–1.64)	(–1.31)	(0.98)	(0.49)	**(3.19)**	**(1.99)**	**(3.26)**	(0.41)
Panel C: Second half of the full sample period (2005:01 – 2014:12)															
(1)	0.037	**0.048**													
	(0.25)	**(2.66)**													
(2)	–0.037	**0.031**	**0.090**	**0.209**	0.058	**0.069**	0.015	–0.001	0.001	**0.004**	–0.002	**0.001**	0.001	0.020	0.005
	(–0.41)	**(2.62)**	**(4.96)**	**(3.40)**	(1.06)	**(3.70)**	(1.44)	(–0.48)	(0.25)	**(2.08)**	(–0.10)	**(1.81)**	(0.69)	(0.72)	(0.29)
Panel D: Good states of the economy (CFNAI > 0)															
(1)	0.324	**0.051**													
	(3.45)	**(4.09)**													
(2)	0.135	**0.033**	**0.101**	**0.220**	**0.093**	**0.068**	–0.009	–0.004	–0.001	0.001	0.004	**0.005**	**0.002**	**0.133**	0.019
	(0.83)	**(3.09)**	**(2.23)**	**(3.59)**	**(1.87)**	**(3.72)**	(–0.16)	(–1.51)	(–0.63)	(0.30)	(0.08)	**(2.50)**	**(2.05)**	**(2.87)**	(0.61)
Panel E: Bad states of the economy (CFNAI < 0)															
(1)	0.091	**0.033**													
	(0.82)	**(2.21)**													
(2)	–0.007	**0.026**	**0.099**	**0.190**	0.048	**0.076**	–0.004	–0.002	–0.001	**0.007**	0.023	**0.003**	0.001	0.060	–0.001
	(–0.05)	**(2.34)**	**(4.04)**	**(2.98)**	(1.14)	**(3.02)**	(–0.09)	(–0.71)	(–0.79)	**(3.41)**	(0.55)	**(2.55)**	(1.03)	(1.56)	(–0.04)

Table 7. *pMAX* by Three Broad Hedge Fund Investment Categories

The first row of this table presents the number of funds existing in each of the three broad hedge fund investment style categories. The second row reports the percentage of hedge funds in total sample for each of the three hedge fund investment styles. The third row reports the cross-sectional average of individual funds' *pMAX* within each category during the full sample period. The fourth row presents, for each investment style separately, the cross-sectional average of the individual funds' time-series standard deviation of *pMAX* during the sample period. The fifth row reports for each investment style the cross-sectional average of the spread between Max and Min of *pMAX*. 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. As can be noticed by reading from left to right, Non-directional category, which includes the Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage hedge fund investment styles have noticeably lower *pMAX*, lower standard deviation of *pMAX*, and lower Max–Min spread of *pMAX* compared to Directional category, which includes the Managed Futures, Global Macro, and Emerging Markets hedge fund investment styles. More importantly, Directional strategies' *pMAX*, standard deviation of *pMAX*, and Max–Min spread of *pMAX* are considerably larger compared to the all hedge fund group as well. Finally, Semi-directional category, which includes the Fund of Funds, Multi Strategy, Long-short Equity Hedge, and Event Driven hedge fund investment styles have *pMAX*, standard deviation of *pMAX*, and Max–Min spread of *pMAX* that are very similar to the all hedge fund group.

	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 *pMAX*	4.05	5.98	9.61	6.56
Avg. Std. Dev. of *pMAX*	1.76	2.43	3.75	2.63
Avg. Max–Min spread of *pMAX*	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 8. Univariate Portfolios of *pMAX* for Three Broad Hedge Fund Categories

For each of the three broad hedge fund investment style categories (Non-directional, Semi-directional, and Directional), univariate quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *pMAX*. Quintile 1 (5) is the portfolio of hedge funds with the lowest (highest) *pMAX* in each hedge fund category. In each column, the top panel reports the average *pMAX* 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 *pMAX* funds) and quintile 1 (low *pMAX* 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.

	Non-Directional Funds Average *pMAX*	Semi-Directional Funds Average *pMAX*	Directional Funds Average *pMAX*
Q1	1.34	1.72	2.64
Q2	2.17	2.98	5.20
Q3	3.07	4.41	7.71
Q4	4.52	6.73	11.28
Q5	10.45	14.08	21.27
	Next-month returns of *pMAX* Quintiles	Next-month returns of *pMAX* Quintiles	Next-month returns of *pMAX* Quintiles
Q1	0.18	0.13	0.09
Q2	0.27	0.34	0.26
Q3	0.42	0.44	0.54
Q4	0.57	0.58	0.58
Q5	0.67	0.82	0.96
Q5 – Q1 Return Diff.	**0.50** **(3.11)**	**0.69** **(3.00)**	**0.88** **(3.71)**
Q5 – Q1 9-factor Alpha Diff.	**0.30** **(2.11)**	**0.40** **(2.43)**	**0.76** **(2.71)**

Table 9. 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 10. Fama-MacBeth Cross-sectional Regressions of Hedge Fund Fees and One-month-ahead Hedge Fund Flows on *pMAX* 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 *pMAX* 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 pMAX with and without control variables:

	Intercept	*pMAX*	SR	STDEV	LagRet	Size	Age	Flow	MgtFee	MinInv	Redemption	DLockup	DLever
(1)	13.378 (142.48)	**0.283** **(20.54)**											
(2)	10.326 (24.89)	**0.251** **(20.05)**	**0.688** **(4.14)**	**0.464** **(12.60)**	–0.006 (–0.68)	0.036 (0.58)	**–0.043** **(–2.55)**	**0.009** **(2.67)**	**1.130** **(7.30)**	**0.041** **(5.72)**	0.001 (0.82)	**3.022** **(46.58)**	**3.555** **(86.56)**

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

	Intercept	*pMAX*	SR	STDEV	LagRet	Size	Age	Flow	IncentFee	MinInv	Redemption	DLockup	DLever
(1)	1.383 (214.92)	**0.012** **(10.12)**											
(2)	1.319 (107.69)	**0.007** **(7.19)**	**–0.042** **(–3.61)**	**0.010** **(2.70)**	–0.002 (–1.32)	–0.013 (–0.86)	**0.002** **(2.69)**	**–0.001** **(–2.76)**	**0.008** **(9.24)**	**–0.006** **(–13.85)**	**–0.002** **(–7.43)**	**–0.148** **(–21.53)**	**0.095** **(11.67)**

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

	Intercept	*pMAX*	SR	STDEV	LagRet	Size	Age	MgtFee	IncentFee	MinInv	Redemption	DLockup	DLever
(1)	–0.410 (–3.75)	**0.020** **(2.96)**											
(2)	–0.535 (–3.61)	**0.026** **(3.76)**	**1.118** **(9.52)**	**–0.189** **(–6.29)**	**0.012** **(1.82)**	0.032 (0.49)	**–0.010** **(–1.79)**	**–0.062** **(–2.05)**	**0.007** **(1.79)**	–0.001 (–0.34)	**0.003** **(3.99)**	**0.165** **(3.55)**	**0.146** **(3.10)**

Table 11. *pMAX* and Mutual Fund Returns

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

Quintile portfolios of mutual funds are formed every month from January 1995 to June 2013 by sorting mutual funds based on their *pMAX*. Quintile 1 is the portfolio of mutual funds with the lowest *pMAX* and quintile 5 is the portfolio of mutual funds with the highest *pMAX*. Panel A reports average *pMAX* 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 *pMAX* and Low *pMAX* 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 *pMAX* 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)

Table 11 (continued)

Panel C. Testing the significance of timing ability

The economic and statistical significance of market- and macro-timing ability for the *high-pMAX* directional, semi-directional, and non-directional hedge funds is tested against the *high-pMAX* mutual funds. In the first row, the average returns and alphas are compared for the *high-pMAX* directional funds (with strong timing ability) vs. the *high-pMAX* mutual funds (with no timing ability). In the second row, the average returns and alphas are compared for the *high-pMAX* semi-directional funds (with semi-strong timing ability) vs. the *high-pMAX* mutual funds (with no timing ability). In the last row, the average returns and alphas are compared for the *high-pMAX* non-directional hedge funds vs. the *high-pMAX* mutual funds (both groups with no timing ability).

	Mutual Funds	
	Return Diff.	4-factor Alpha Diff.
Directional Hedge Funds	**0.50**	**0.82**
	(2.15)	**(3.38)**
Semi-directional Hedge Funds	**0.33**	**0.57**
	(1.97)	**(5.77)**
Non-directional Hedge Funds	0.23	**0.65**
	(0.89)	**(4.73)**

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Online Appendix

To save space in the paper, we present some of our findings in the Online Appendix. Section I describes the mutual fund database and reports the number of mutual funds, yearly attrition rates, and their summary statistics. Table I examines the persistence of *pMAX* using fund-level Fama-MacBeth cross-sectional regressions of *pMAX* on lagged predictor variables. Table II presents 5x5 conditional (sequentially) sorted bivariate quintile portfolio analysis of *pMAX* and STDEV. Table III reports results from sorting individual hedge funds into univariate quintile portfolios based on their *pMAX*/STDEV ratios. Table IV presents 5x5 conditional (sequentially) sorted bivariate quintile portfolio analysis of *pMAX* and the appraisal ratio. Table V investigates the predictive power of *pMAX* over future hedge fund returns with two alternative multivariate Fama-MacBeth specifications of future hedge fund returns on *pMAX* and control variables. Table VI examines the long-term predictive power of *pMAX* and reports the next 3-, 6-, 9-, and 12-month-ahead returns of quintile portfolios of hedge funds sorted by *pMAX*. Table VII presents summary statistics for the mutual funds database.

This Version: July 2015

I. Mutual Fund Database

This study uses 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 V 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 V 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 V 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.

Table I. Fama-MacBeth Cross-sectional Regressions of 12-month-ahead *pMAX* on Current *pMAX* and Other Fund Characteristics

This table reports the average intercept and average slope coefficients from the Fama-MacBeth cross-sectional regressions of 12-month-ahead *pMAX* on current *pMAX* and other fund characteristics. Fama-MacBeth regressions are run for each month, and the average slope coefficients are calculated for the period January 1995–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.

Intercept	*pMAX*	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)**
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)**
2.092	**0.489**	**0.172**	**1.217**	**0.028**	0.016	–0.033	**0.001**	**0.038**	0.071	**–0.009**	0.001	**0.293**	**0.134**	**38.14%**
(5.02)	**(25.54)**	**(2.47)**	**(18.18)**	**(2.75)**	(0.18)	(–1.25)	**(1.79)**	**(7.76)**	(1.69)	**(–2.92)**	(0.06)	**(4.25)**	**(4.07)**	**(41.85)**

Table II. Bivariate Portfolios of *pMAX* controlling for STDEV

This table presents 5x5 conditional (sequentially) sorted bivariate portfolio analysis of *pMAX* 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 *pMAX*. The last column presents the next-month returns of *pMAX* 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-*pMAX* funds and Low-*pMAX* 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 *pMAX*	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 *pMAX*	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 III. Univariate Portfolios of Hedge Funds Sorted by *pMAX*/STDEV

Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds based on their *pMAX/*STDEV ratios. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX/*STDEV ratio, and quintile 5 is the portfolio of hedge funds with the highest *pMAX/*STDEV ratio. The table reports average *pMAX/*STDEV ratio in each quintile, the next month average returns, and the 9-factor alphas for each quintile. The last row shows the average monthly return difference and the 9-factor alpha difference between High-*pMAX* and Low-*pMAX* 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.

Quintiles	Average *pMAX/*STDEV in each Quintile	Next Month Average Returns	Next Month 9-Factor Alphas
Q1	1.19	0.05	–0.17
		(0.26)	(–1.36)
Q2	1.67	**0.40**	**0.21**
		(2.44)	**(1.96)**
Q3	1.99	**0.55**	**0.29**
		(3.28)	**(2.34)**
Q4	2.35	**0.61**	**0.40**
		(4.28)	**(3.37)**
Q5	3.28	**0.64**	**0.52**
		(7.81)	**(6.83)**
Q5 – Q1		**0.59**	**0.68**
t-statistic		**(4.42)**	**(5.17)**

Table IV. Bivariate Portfolios of *pMAX* controlling for the Appraisal Ratio (AR)

This table presents 5x5 conditional (sequentially) sorted bivariate portfolio analysis of *pMAX* and the appraisal ratio. Quintile portfolios are formed every month from January 1995 to December 2014 by sorting hedge funds first based on the 9-Factor Appraisal Ratio (AR). Then, within each AR-sorted portfolio, hedge funds are further sorted into sub-quintiles based on their *pMAX*. The last column presents the next-month returns of *pMAX* quintile portfolios averaged across the AR quintiles. The last two rows show the monthly average return differences and the 9-factor alpha differences between High-*pMAX* funds and Low-*pMAX* funds within each AR 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.

	Low AR	Q2	Q3	Q4	High AR	Averaged across AR quintiles
Low *pMAX*	-0.31	-0.01	0.10	0.19	0.23	0.04
Q2	0.04	0.25	0.30	0.38	0.47	0.29
Q3	0.12	0.35	0.43	0.46	0.57	0.39
Q4	0.18	0.42	0.59	0.69	0.77	0.53
High *pMAX*	0.43	0.53	0.84	0.90	0.93	0.73
Return Diff.	**0.75**	**0.54**	**0.74**	**0.71**	**0.69**	**0.69**
	(3.33)	**(2.33)**	**(3.08)**	**(3.25)**	**(3.60)**	**(3.46)**
Alpha Diff.	**0.53**	0.38	**0.56**	**0.53**	**0.53**	**0.50**
	(2.13)	(1.53)	**(2.16)**	**(2.55)**	**(2.91)**	**(2.60)**

Table V. Fama-MacBeth Cross-sectional Regressions of Hedge Fund Returns on *pMAX* 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 *pMAX* 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 (in Panel A) as well as for two subsample periods (Panels B and C) and for good and bad states of the economy (Panels D and E). 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	*pMAX*	SR	AVRG	STDEV	LagRet	Size	Age	Flow	IncentFee	MgtFee	MinInv	Redemption	DLockup	DLever
Panel A: Full sample period (1995:01 – 2014:12)															
(1)	0.088	**0.029**		**0.226**	**0.065**	**0.072**	–0.004	–0.003	–0.001	**0.004**	0.012	**0.004**	**0.002**	**0.101**	0.010
	(0.82)	**(3.27)**		**(5.58)**	**(1.80)**	**(5.59)**	(–0.11)	(–1.66)	(–1.02)	**(1.94)**	(0.40)	**(3.45)**	**(2.31)**	**(3.16)**	(0.54)
(2)	0.054	**0.032**	**0.090**	**0.163**		**0.071**	–0.006	–0.003	–0.001	**0.005**	0.011	**0.004**	**0.001**	**0.105**	0.014
	(0.49)	**(3.45)**	**(3.46)**	**(3.74)**		**(5.31)**	(–0.18)	(–1.61)	(–1.03)	**(2.34)**	(0.36)	**(3.10)**	**(1.84)**	**(3.24)**	(0.76)
Panel B: First half of the full sample period (1995:01 – 2004:12)															
(1)	0.199	**0.027**		**0.222**	0.074	**0.075**	–0.023	–0.006	–0.001	0.004	0.028	**0.007**	**0.003**	**0.176**	0.014
	(1.02)	**(2.05)**		**(3.97)**	(1.58)	**(4.14)**	(–0.34)	(–1.67)	(–1.21)	(0.99)	(0.46)	**(3.35)**	**(2.27)**	**(3.28)**	(0.47)
(2)	0.156	**0.030**	**0.090**	**0.160**		**0.073**	–0.027	–0.006	–0.001	0.004	0.028	**0.006**	**0.002**	**0.181**	0.019
	(0.77)	**(2.18)**	**(1.88)**	**(2.79)**		**(3.88)**	(–0.39)	(–1.62)	(–1.26)	(1.32)	(0.46)	**(3.09)**	**(1.83)**	**(3.34)**	(0.60)
Panel C: Second half of the full sample period (2005:01 – 2014:12)															
(1)	–0.023	**0.030**		**0.230**	0.055	**0.069**	0.016	–0.001	0.001	**0.005**	–0.003	**0.001**	0.001	0.026	0.005
	(–0.26)	**(2.57)**		**(3.90)**	(1.00)	**(3.72)**	(1.47)	(–0.50)	(0.46)	**(2.10)**	(–0.14)	**(1.77)**	(0.84)	(0.92)	(0.26)
(2)	–0.048	**0.034**	**0.090**	**0.167**		**0.068**	0.014	–0.001	0.001	**0.005**	–0.005	0.001	0.001	0.030	0.008
	(–0.54)	**(2.67)**	**(4.33)**	**(2.50)**		**(3.58)**	(1.31)	(–0.35)	(0.52)	**(2.40)**	(–0.26)	(1.20)	(0.61)	(1.00)	(0.49)
Panel D: Good states of the economy (CFNAI > 0)															
(1)	0.177	**0.030**		**0.240**	**0.085**	**0.068**	–0.005	–0.004	–0.001	0.001	0.003	**0.005**	**0.002**	**0.138**	0.019
	(1.09)	**(2.84)**		**(4.14)**	**(1.71)**	**(3.70)**	(–0.08)	(–1.56)	(–0.56)	(0.27)	(0.06)	**(2.67)**	**(2.38)**	**(2.99)**	(0.63)
(2)	0.141	**0.036**	**0.085**	**0.167**		**0.064**	–0.006	–0.004	–0.001	0.002	–0.001	**0.004**	**0.002**	**0.143**	0.026
	(0.85)	**(3.19)**	**(1.90)**	**(2.89)**		**(3.54)**	(–0.10)	(–1.49)	(–0.43)	(0.64)	(–0.01)	**(2.33)**	**(1.92)**	**(3.05)**	(0.83)
Panel E: Bad states of the economy (CFNAI < 0)															
(1)	–0.002	**0.027**		**0.212**	0.044	**0.076**	–0.003	–0.002	–0.001	**0.008**	0.022	**0.003**	0.001	0.063	–0.001
	(–0.01)	**(2.46)**		**(3.48)**	(1.05)	**(3.01)**	(–0.07)	(–0.68)	(–0.71)	**(3.47)**	(0.52)	**(2.68)**	(1.23)	(1.67)	(–0.01)
(2)	–0.034	**0.027**	**0.096**	**0.159**		**0.077**	–0.007	–0.002	–0.001	**0.008**	0.023	**0.003**	0.001	**0.068**	0.001
	(–0.25)	**(2.26)**	**(3.64)**	**(2.50)**		**(3.02)**	(–0.17)	(–0.65)	(–0.81)	**(3.84)**	(0.53)	**(2.36)**	(0.84)	**(1.72)**	(0.04)

Table VI. Long-term Predictive Power of *pMAX*

Quintile portfolios are formed each month by sorting hedge funds based on their *pMAX* measures. Quintile 1 is the portfolio of hedge funds with the lowest *pMAX* and quintile 5 is the portfolio of hedge funds with the highest *pMAX*. This table reports the next 3-month, 6-month, 9-month, and 12-month average returns for each of the five quintiles. The last two rows show the monthly average return differences and the 9-factor alpha differences between quintile 5 (*high-pMAX* funds) and quintile 1 (*low-pMAX* funds). Average returns and alphas are defined in monthly percentage terms. Newey-West *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

	3-month ahead returns of *pMAX* Quintiles	6-month ahead returns of *pMAX* Quintiles	9-month ahead returns of *pMAX* Quintiles	12-month ahead returns of *pMAX* Quintiles
Q1	0.12	0.14	0.15	0.16
Q2	0.35	0.34	0.31	0.31
Q3	0.45	0.44	0.40	0.38
Q4	0.55	0.48	0.46	0.44
Q5	0.72	0.64	0.56	0.53
Q5 – Q1 Return Diff.	**0.60** **(3.42)**	**0.49** **(3.13)**	**0.41** **(2.68)**	**0.37** **(2.47)**
Q5 – Q1 9-factor Alpha Diff.	**0.39** **(2.29)**	**0.33** **(2.11)**	**0.30** **(2.04)**	0.25 (1.60)

Table VII. 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