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The Impact of Quantitative Methods on Hedge Fund Performance

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Abstract

In the last 20 years, the amount of assets managed by quantitative and qualitative hedge funds have grown dramatically. We examine the difference between quantitative and qualitative hedge funds in a variety of ways, including management differences and performance differences. We find that both quantitative and qualitative hedge funds have positive risk-adjusted returns. We also find that overall, quantitative hedge funds as a group have higher αs than qualitative hedge funds. The outperformance might be as high as 72 bps per year when considering all risk factors. We also suggest that this additional performance may be due to better timing ability.

Keywords: *quantitative portfolio management, alpha, hedge funds, returns*

JEL classification: *G*0, *G*10, *G*11, *G*23

1. Introduction

In the last few years, quantitative portfolio management and quantitative *equity* portfolio management have been on the rise (see Figure 1). The total assets managed by quantitative funds grew by 807% from \$9.98 to \$90.48 billion, while the assets managed by qualitative funds grew by 609% from \$18.61 billion to \$131.92 billion over the period from 1994 to 2009.[1] The growth in this method of investing can be attributed to many factors, but perhaps four of them stand out. First, there has been an advancement in the knowledge and

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[1] These numbers represent the numbers in the HFR database and not the actual numbers of the entire industry.

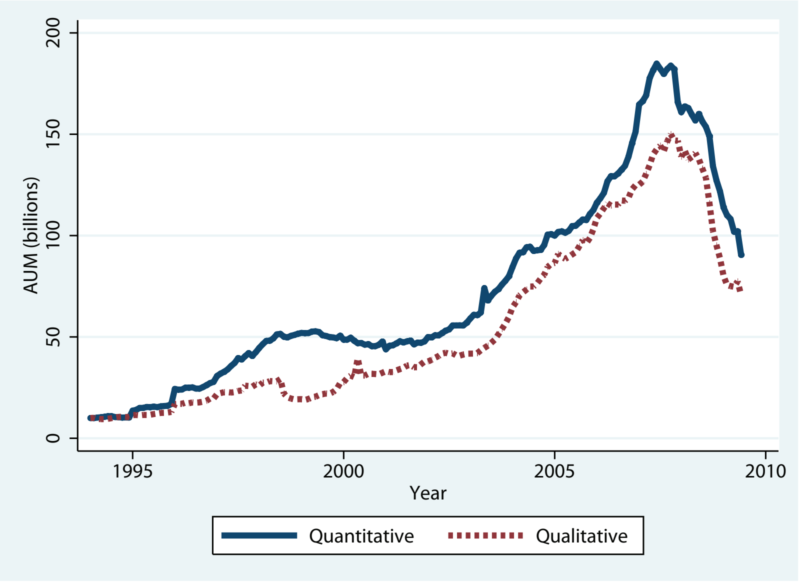

Fig. 1. The growth of quantitative and qualitative funds.

This figure represents the growth in assets under management (AUM) for quantitative and qualitative hedge funds in billions of dollars. The qualitative funds initial value was normalised to the value in the database of quantitative funds as of January 1994 at $9.98B. Qualitative fund total on this date was $18.61B.

tools for assessing financial markets quantitatively. Second, there has been a dramatic improvement in the technology required to efficiently examine the markets quantitatively. Third, there has been an increasing demand from pension funds and other large institutional investors for an *investment process*. Quantitative investing lends itself more easily to a more structured investment process. Fourth, some have argued that a quantitative disciplined investment process might lead to superior returns than a less quantitative investment process. In particular, Chincarini and Kim (2006) have discussed the potential advantages and disadvantages of quantitative funds (Table 1) arguing that the advantages most likely outweigh the disadvantages.

This paper is focused on addressing the last of these potential reasons for the growth in quantitative portfolio management. In particular, we attempt to study the performance characteristics of quantitative and qualitative hedge funds. The advantages for quantitative funds include the breadth of selections, the elimination of behavioral errors (which might have been particularly important during the financial crisis of 2008), and the potential lower administration costs (after hedge fund fees). The disadvantages for quantitative hedge funds include the reduced use of qualitative types of data, the reliance on historical data, and the lacking of an ability to quickly react to new economic paradigms. Finally, there is the potential of data mining, which will lead to strategies that aren't as effective once implemented. In this paper, we focus primarily on examining the return differences rather than attempting to detail which of the advantages or disadvantages is central to the return differences.

There has been a vast amount of research to measure and understand hedge fund performance (Agarwal and Naik, 2004; Liang, 1999, 2001; Edwards and Caglayan, 2001). Recently, Agarwal *et al*. (2013) show that the confidential holdings of hedge

Table 1

The advantages and disadvantages of quantitative versus qualitative portfolio management

This table presents the advantages and disadvantages to quantitative and qualitative investing. High or low is used to indicate if a specific style of portfolio management has a high or low exposure to a particular criteria. Objectivity represents the ability to remain objective and non-emotional in trading, Breadth represents the ability to easily examine large amounts of securities for inclusion in the portfolio, Behavioural Errors indicates the possibility to make human behavioural errors in selecting securities, Replicability represents the ability to transfer the portfolio building knowledge to another entity, Costs represents the costs required to manage the portfolio, Controlled risk represents the ability to precisly quantify the risk in the strategies, Qualitative Inputs represents the ability to select securities based on non-quantitative data, Historical Data Reliance represents the degree to which the portfolio relies on historical data patterns to choose securities, Data Mining represents the tendency for the security selection to have been based on data mined research, and Reactivity represents the ability of the security selection procedure to react quickly to new paradigms or market events.
Source: Chincarini and Kim (2006).

Advantages		
Criteria	Quantitative	Qualitative
Objectivity	High	Low
Breadth	High	Low
Behavioural Errors	Low	High
Replicability	High	Low
Costs	Low	High
Controlled Risk	High	Low
Disadvantages		
Criteria	Quantitative	Qualitative
Qualitative Inputs	Low	High
Historical Data Reliance	High	Low
Data Mining	High	Low
Reactivity	Low	High

funds as measured by amendments to their 13-F filings provide superior performance to the rest of the holdings of hedge fund portfolios. Jame (2012) examines the daily trading of hedge funds and does not find abnormal returns for the average hedge fund, but finds outperformance for the top decile of hedge funds. Sadka (2012) shows that hedge funds that load on liquidity risk have significantly higher returns and this could explain the higher alphas in the hedge fund industry. Chen *et al*. (2012) use an expectation-maximisation algorithm and find that about 50% of hedge funds have positive skill and that these funds deliver superior out-of-sample alpha. Ammann *et al*. (2013) use probit regressions to identify characteristics that might be related to performance persistence. They find statistically significant performance persistence for up to 36 months. Tudor and Cao (2012) study the ability of hedge funds to produce absolute performance and find that certain hedge fund strategies have a better probability of producing absolute performance.

Many papers find positive market timing ability of hedge funds (Chen, 2007; Chen and Liang, 2007; Chincarini and Nakao, 2011; Chincarini, 2012a; Li and Shawky, 2013; Cao *et al*., 2013), although some do not find any market timing ability (Park, 2010).

Several papers have investigated the causes for hedge fund excess performance. Bali *et al*. (2011, 2012) find that a hedge fund's exposure to systemic macroeconomic risk factors helps predict its subsequent returns. Duanmu *et al*. (2013) build upon this work and show that beta-active hedge fund managers do better than alpha-active hedge fund managers. Bali *et al*. (2013) show that certain hedge fund strategies outperform stocks and bonds using a stochastic dominance criterion.

Some studies have examined hedge fund returns in more detail to determine whether hedge funds offer market neutral or hedged investing (Asness *et al*., 2001; Patton, 2009; and Titman and Tiu, 2011). New research has focused on the copycat behaviour of hedge funds (Chincarini, 2012b) and has found that immediately after the 13-F releases of hedge fund holdings, there is copycat behaviour by other funds who buy these holdings, even though the long-term return benefit does not seem to exist (Brown and Schwarz, 2013). There are notable differences in the management structure of hedge funds, including their terms of liquidity. Aiken *et al*. (2013) have found that hedge fund gates do not always protect investors and may be associated with poor performance, while Teo (2011) finds that conditional on liquidity, hedge funds gates improve performance.

There is also a fair amount of new research on the reliability of hedge fund return data. Itzhak *et al*. (2012) find evidence that hedge funds manipulate stock prices near quarter end to improve their return performance. Patton *et al*. (Forthcoming) find that the revision of historical returns by hedge funds is not random and is partly predictable, which might introduce biases in hedge fund return data. Joenväärä *et al*. (2013) aggregate many of the existing hedge fund databases and uncover a host of interesting biases related to the performance of hedge funds.

Ang *et al*. (2011) study the behaviour of hedge fund leverage over the business cycle, while Lan *et al*. (2011) construct a theoretical model to understand how a hedge fund's alpha, fee structure, leverage and returns might be related.

The contribution of this paper is to extend the literature on understanding whether the type of portfolio management style leads to different return performance. Specifically, this paper analyses whether hedge funds that use more quantitative techniques produce better returns than other hedge funds.

The paper is organised as follows: section 2 describes the hedge fund database used in this study; section 3 discusses the differences between quantitative and qualitative hedge funds in terms of fund characteristics, including fees, average age, investability, liquidity, transparency, and legal structure; section 4 discusses the performance models used to test for differences in ability between quantitative and qualitative managers and presents those results; and section 6 concludes the paper.

2. Data

The hedge fund data used for this paper was obtained from Hedge Fund Research, which is one of the most extensive and reliable hedge fund databases used by practitioners. It is also used by academics, but to a lesser extent than TASS and CISDM. The hedge fund data covers the period January 1970 to June 2009. The data on factors is for the period January 1994 to March 2009.[2]

[2] This was a limitation of the data at the time of the writing of this paper.

2.1. *Data biases*

It is well known that the leading hedge fund databases, including HFR, did not collect information on *disappearing* funds prior to 1994. Thus, all data prior to 1994 is dropped from the analysis. Although all hedge fund databases may be subject to survivorship bias (Brown *et al*., 1992, 1999; Ackermann *et al*., 1999), some authors have argued that this bias might be larger in HFR (Liang, 2000). The main goal of this paper is to study the relative performance of quantitative and qualitative hedge funds. Thus, to the extent that any survivorship bias not accurately accounted for in this database is symmetric between funds, it should not affect the analysis in this paper. Nevertheless, both live and dead funds are used in this study to reduce the impact of survivorship bias and the results are presented over various sample periods and divisions of the data.

Other well-known biases that exist in hedge fund databases are also not a problem for this comparative study, including selection bias, backfill bias or instant history bias,[3] double-counting bias, and reporting bias (Fung and Hsieh, 1997; Kosowski *et al*., 2007; Agarwal *et al*., 2013; Agarwal and Jorion, 2010; Boyson, 2008).

2.2. *Sample statistics*

Table 2 reports the summary statistics for all of the hedge fund data, excluding fund-of-funds. The summary statistics are presented for both the live and dead funds separately and together.

As of June 2009, the HFR database contained a total of 10,007 hedge funds (excluding fund-of-funds of which there were 3,798). This is comprised of 5,501 dead funds (of that total, 2,766 are liquidated funds and 2,735 are non reporting funds) and 4,506 live funds with the live funds comprising a total of $913.54 billion in assets under management. The HFR database classifies hedge funds into various categories based upon their investment strategy. There are five broad categories and sub-categories within those: Equity Hedge,[4] Event-Driven,[5] Macro,[6] Relative Value,[7] and Fund of Funds.[8]

We further reduce the data by eliminating funds that only report quarterly (97 funds were dropped), since we are using monthly returns in our performance analysis. We also dropped funds that did not have 36 consecutive months of data, since we felt that would be a minimum number of observations to run Newey-West corrected regressions.

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[3] The typical fix for backfill bias is to drop the first 12 or 24 months of a hedge fund's returns in the database.

[4] Sub-Categories are Energy/Basic Materials, Equity Market Neutral, Fundamental Growth, Fundamental Value, Quantitative Directional, Short Bias, Technology/Health Care, Multi-Strategy.

[5] Subcategories are Activist, Credit Arbitrage, Distressed/Restructuring, Merger Arbitrage, Private Issue/Regulation D, Special Situations, Multi-Strategy.

[6] Subcategories are Active Trading, Commodity Discretionary, Commodity Systematic, Currency Discretionary, Commodity Systematic, Discretionary Thematic, Systematic Diversified, Multi-Strategy.

[7] Subcategories are Fixed Income-Asset Backed, Fixed Income-Convertible Arbitrage, Fixed Income-Corporate, Fixed Income-Sovereign, Volatility, Yield Alternatives, Multi-Strategy.

[8] Subcategories are Conservative, Diversified, Market Defensive, and Strategy.

Table 2

Hedge fund database summary statistics

This table reports the time-series averages of annual cross-sectional averages from January 1994 to March 2009. Avg. Number is the average number of hedge funds across monthly observations, Avg. AUM represents the average assets under management across months in millions of U.S. dollars, Avg. Growth computes the average growth rate of new assets into the average hedge fund using the formula for monthly growth in flows as: $g_t = \frac{\text{New Flows}_t}{AUM_{t-1}}$, where $\text{New Flows}_t = \text{AUM}_t - \text{AUM}_{t-1} \cdot (1 + \tilde{r}_{it})$, where r_{it} is the net returns of fund i from $t-1$ to t, Avg. M. Fee is the average management fee across hedge funds, Avg. I. Fee is the average incentive fee across hedge funds, Avg. Age is the average number of years of existence of a fund in a particular category, High Water (%) is the percentage of hedge funds in the database with a high water mark across funds and time, and Hurdle Rate (%) is the percentage of funds with a hurdle rate across funds and time.

Group	Total Number	Avg. Number	Avg. AUM	Avg. Growth	Avg. M. Fee	Avg. I. Fee	Avg. Age	High Water (%)	Hurdle Rate (%)
Equity Hedge	3348	1413.73	102.62	0.15	1.34	18.91	6.92	89.67	13.71
EH:Engy/Bmat	134	47.56	88.27	0.04	1.45	20.13	5.80	91.79	10.45
EH:EqMktNeu	472	188.17	111.59	0.20	1.35	19.46	6.50	87.50	22.67
EH:FndmtlGr	775	337.97	90.95	0.05	1.39	18.44	7.11	87.35	16.65
EH:FndmtlVal	1337	581.72	112.64	0.26	1.32	19.47	6.99	94.02	9.80
EH:QuantDir	296	117.63	142.36	0.05	1.28	16.16	7.35	76.01	15.54
EH:Short Bias	43	21.07	25.24	0.05	1.23	18.40	8.98	81.40	4.65
EH:Tech/Hlth	235	94.72	59.75	0.03	1.33	19.56	6.43	93.19	10.21
EH:MultStrat	56	24.90	33.43	0.05	1.14	19.29	7.08	94.64	10.71
Event-Driven	622	285.19	163.46	0.05	1.46	19.67	7.54	95.02	7.72
ED:Activist	23	9.66	194.02	0.04	1.72	20.00	6.62	100.00	8.70
ED:CreditArb	23	7.50	132.51	0.04	1.56	20.00	5.15	100.00	4.35
ED:Dstrd/Rstrc	180	84.97	171.71	0.03	1.46	19.03	7.75	95.00	6.67
ED:MergerArb	91	48.74	109.54	0.02	1.26	19.40	8.68	92.31	9.89
ED:PvIss/RegD	38	14.89	70.12	0.04	1.70	20.58	5.59	97.37	2.63
ED:SpecialSit	257	113.92	164.85	0.08	1.47	19.92	7.36	95.33	8.17
ED:Mult-Strat	10	6.66	582.65	0.02	1.83	24.43	12.73	80.00	20.00
Macro	1263	542.34	129.75	0.12	1.88	19.15	7.33	84.88	9.58
M:ActiveTrd	29	12.16	154.47	0.07	3.00	20.00	6.91	100.00	3.45
M:CmdtyDiscr	18	7.71	45.71	0.06	1.75	20.00	6.38	66.67	5.56
M:CmdtySys	71	30.78	61.65	0.04	1.37	12.21	7.09	74.65	19.72
M:CrrcyDiscr	19	9.32	104.35	0.25	2.00	20.00	7.93	89.47	10.53
M:CrrcySystm	161	68.58	221.59	0.06	1.80	20.19	7.41	82.61	8.70
M:DscrThm	287	115.50	154.63	0.11	1.66	18.95	6.66	95.47	11.50
M:SysDivrsf'd	588	261.02	103.49	0.10	2.06	19.30	7.80	80.10	5.95
M:Mult-Strat	90	37.69	190.72	0.35	1.57	20.00	6.68	92.22	23.33
Relative Val	1119	459.21	155.51	0.06	1.37	18.60	6.67	84.18	17.43
RV:FI-AsstBkd	135	58.47	146.28	0.08	1.23	18.78	6.84	85.19	22.96
RV:FI-CnvArb	210	100.96	116.08	0.03	1.33	18.24	7.94	82.86	14.76
RV:FI-Corp	213	80.65	203.97	0.04	1.32	17.98	6.32	81.69	16.43
RV:FI-Sovergn	37	14.54	137.84	0.05	1.29	20.00	6.27	81.08	37.84
RV:Volatility	81	27.51	45.47	0.05	1.59	20.00	5.35	93.83	2.47
RV:YieldAlt	53	17.52	44.17	0.07	1.27	18.33	5.26	77.36	22.64
RV:Mult-Strat	390	159.56	191.50	0.08	1.45	18.92	6.63	85.13	17.95
Live Funds	3198	1476.05	146.17	0.14	1.52	19.24	7.43	91.59	12.66
Dead Funds	3154	1224.43	87.91	0.09	1.45	18.94	6.60	84.91	13.25
All	6352	2700.48	123.86	0.12	1.46	18.97	7.02	88.27	12.96

Unfortunately, a total of 3,516 funds were dropped due to this. Across fund categories, 52% were from Equity Hedge, 9% from Event-Driven, 21% from Macro, and 18% from Relative Value. Of the funds that were dropped, 1,288 (or 37%) came from Active funds. These consisted of newer funds that existed for less than 3 years. Another 1,190 (34%) came from liquidated funds and 1,038 (29%) came from non-reporting, but existing funds. Finally, we dropped funds for which the performance numbers were missing or they did not have consecutive monthly return data (44 funds).[9] This left a final data set of 6,353 hedge funds with about 53% from Equity Hedge, 10% from Event-Driven, 20% from Macro, and 17% from Relative Value. Finally, we dropped all observations prior to 1994 given the aforementioned issues with survivorship bias. The final data set consisted of a total of 6,352 hedge funds.

2.3. *Classification of quantitative and qualitative hedge funds*

We realise that most hedge funds are neither strictly quantitative (quant) or strictly qualitative (qual). However, the goal of this paper is to make an attempt at sorting the two types of funds. Thus, if the quantitative group of funds generally uses more quantitative investment techniques than the qualitative group, we may learn about the relative importance of quantitative techniques.

In the hedge fund database, funds are classified according to their *main strategy* and their *sub-strategy*. For each individual hedge fund, the database has a fund description. We use both of these data sources to construct two classifications of quantitative and qualitative hedge funds.

2.3.1. *Classification 1.* For this classification method, we read all the hedge fund category descriptions and divided the hedge funds according to Table 3.

Of all the hedge fund sub-categories, we classified 10 as quantitative or qualitative and did not categorise 18 of them. Of the ones categorised, we used either the strategy name and/or description to determine whether the funds were quantitative or qualitative hedge funds.[10] Our main method used to classify each fund group was to look for the term *quantitative* or a description of a similar nature to place a fund in the quantitative category. We also looked for words like *discretionary* to classify qualitative funds and *systematic* to classify quantitative funds. Of the four main hedge fund categories, we only found two of them reliable enough to classify. Thus, in the Equity Hedge category, we classified Equity Market Neutral and Quantitative Directional as quantitative hedge funds and Fundamental Growth and Fundamental Value as qualitative categories. In the Macro category, we classified Commodity Systematic, Currency Systematic, and Systematic Diversified as quantitative funds and Commodity Discretionary, Currency Discretionary, and Diversified Thematic as qualitative funds. We did not classify any of the Event Driven funds since these funds varied too substantially within the category and it was not clear

[9] This can be for a variety of reasons. One of the most common reasons is that a fund begins reporting quarterly, but at a later date reports monthly. Thus, in the database, the fund is classified as a monthly reporter, even though for a portion of its existence it was a quarterly reporter.

[10] The strategy descriptions are available directly from HFR (www.hedgefundresearch.com) or from the authors upon request.

Table 3

Classification 1 of quantitative and qualitative funds

This table reports the HFR hedge fund strategies that were classified as quantitative or qualitative. Main represents the main hedge fund category and sub represents the sub-category within the main category according to HFR. *Source*: HFR strategy descriptions and authors' judgement. For a full description of each fund main category and sub-category, see Chincarini and Nakao (2011).

Categorised			
		Quantitative	Qualitative
Number	Main	Sub	Sub
1.	Equity Hedge		
		EH: Equity Market Neutral	EH: Fundamental Growth
		EH: Quantitative Directional	EH: Fundamental Value
2.	Macro		
		M: Commodity Systematic	M: Commodity Discretionary
		M: Currency Systematic	M: Currency Discretionary
		M: Systematic Diversified	M: Discretionary Thematic

from the category descriptions how to separate quantitative and qualitative funds. We also did not classify any of the Relative Value funds, even though many of these funds use quantitative techniques, because the broader category descriptions left us no clear cut way to divide them. We also left out a couple of Macro funds that could not be easily divided on category description alone.

2.3.2. *Classification 2.* In order to check our results against other methods of separating quantitative and qualitative hedge funds, we considered all hedge funds again, but performed a word search on the strategy description of each individual hedge fund in the database. We classified a fund as quantitative if the following words appeared in the fund description: *quantitative*, *mathematical*, *model*, *algorithm*, *econometric*, *statistic*, or *automate*. Also, the fund description could not contain the word *qualitative*. We classified a fund as qualitative if it contained the word *qualitative* in its description or had none of the words mentioned for the quantitative category.

The bulk of the analysis in this paper is conducted with classification 1, however in the regression analysis (the most important part of the performance analysis), we present the results for both classification method 1 and classification method 2.

3. Management Differences

Table 4 produces some broad management characteristics of the quantitative and qualitative hedge funds using classification 1. This information is from the HFR database as of June 2009. First, there are many more non-quantitative hedge funds in our study. This is both true as of June 2009 as well as on average across time (see the Avg. Number column). Second, the average assets under management (AUM) over the entire time period is about the same for quantitative and qualitative funds. We also created a measure of the growth in new assets over the entire period for each hedge fund. We computed the

Table 4

Characteristics of quantitative and qualitative hedge funds I

This table reports the time-series averages of annual cross-sectional averages from January 1994 to March 2009. C1 refers to classification 1 for quantitative and qualitative funds, while C2 refers to classification 2. Avg. Number is the average number of hedge funds across monthly observations, Avg. AUM represents the average assets under management across months in millions of U.S. dollars, Avg. Growth computes the average growth rate of new assets into the average hedge fund using the formula for monthly growth in flows as: $g_t = \frac{\text{New Flows}_t}{AUM_{t-1}}$, where New $\text{Flows}_t = \text{AUM}_t - \text{AUM}_{t-1} \cdot (1 + \tilde{r}_{it})$, where $\tilde{r}_{it}$ is the net-of-fee returns of fund i from $t-1$ to t minus the risk-free rate, Avg. M. Fee is the average management fee across hedge funds, Avg. I. Fee is the average incentive fee across hedge funds, Avg. Age is the average number of years of existence of a fund in a particular category, High Water (%) is the percentage of hedge funds in the database with a high water mark across funds and time, and Hurdle Rate (%) is the percentage of funds with a hurdle rate across funds and time.

Group	Total Number	Avg. Number	Avg. AUM	Avg. Growth	Avg. M. Fee	Avg. I. Fee	Avg. Age	High Water (%)	Hurdle Rate (%)
Quantitative (C1)	1588	666.18	119.85	0.11	1.64	18.65	7.26	81.55	13.60
Qualitative (C1)	2436	1051.79	110.46	0.17	1.39	19.08	6.99	91.83	12.15
Quantitative (C2)	1040	449.26	111.73	0.07	1.54	19.64	6.95	92.69	12.69
Qualitative (C2)	5248	2226.11	125.55	0.13	1.45	18.86	7.04	87.37	13.01
Quant. Sub. (C1)									
EH:EqMktNeu	472	188.17	111.59	0.20	1.35	19.46	6.50	87.50	22.67
EH:QuantDir	296	117.63	142.36	0.05	1.28	16.16	7.35	76.01	15.54
M:CmdtySys	71	30.78	61.65	0.04	1.37	12.21	7.09	74.65	19.72
M:CrrcySystm	161	68.58	221.59	0.06	1.80	20.19	7.41	82.61	8.70
M:SysDivrsf'd	588	261.02	103.49	0.10	2.06	19.30	7.80	80.10	5.95
Qual. Sub. (C1)									
EH:FndmtlGr	775	337.97	90.95	0.05	1.39	18.44	7.11	87.35	16.65
EH:FndmtlVal	1337	581.72	112.64	0.26	1.32	19.47	6.99	94.02	9.80
M:CmdtyDiscr	18	7.71	45.71	0.06	1.75	20.00	6.38	66.67	5.56
M:CrrcyDiscr	19	9.32	104.35	0.25	2.00	20.00	7.93	89.47	10.53
M:DscrThm	287	115.50	154.63	0.11	1.66	18.95	6.66	95.47	11.50

average growth rate of new assets into the average hedge fund using the formula for monthly growth in flows as: $g_t = \frac{\text{New Flows}_t}{AUM_{t-1}}$, where New $\text{Flows}_t = \text{AUM}_t - \text{AUM}_{t-1} \cdot (1 + \tilde{r}_{it})$ and $\tilde{r}_{it}$ is the net returns of fund i from $t-1$ to t (Sirri and Tufano, 1998). Using this measure, we find that on average across time and across funds, the average qualitative fund has had an average growth in assets of 17% per month compared to quantitative funds of 11% using our classification 1 for quantitative funds. Using classification 2 does not change the qualitative results, the average growth of qualitative assets is about 13% compared to 7% for quantitative funds. Part of this result may be due to the fact that there are many more qualitative funds for investors to choose from. However, the actual assets in quantitative funds as a whole was \$9.98 billion in January 1994, while for qualitative it was \$18.61 billion. By June 2009, the numbers were \$90.48 billion and \$131.92 billion respectively. Thus, the total asset growth of quantitative funds over the period was higher by almost 25%. This was due to their much better performance and other factors, like fund attrition, not due to asset flows.[11] Third, the average management fee does not differ too much, but is higher for the average quantitative fund. The average incentive fee is higher or lower depending on which classification method is used. Fourth, of all the quantitative funds, 82% have high water marks, while 92% of the qualitative funds have high water marks using classification 1.[12] Quantitative funds have about the same percentage of funds with hurdle rates.[13]

In the same table, we breakdown the statistics by hedge fund sub-strategy. The items of note are that Equity Market Neutral funds have had by far the largest AUM growth amongst quantitative funds, while Fundamental Value and Currency Discretionary have had the highest AUM growth for the qualitative category.

Table 5 contains other characteristics of these hedge fund categories. The average minimum investment for quantitative funds is much higher than for qualitative funds ($1.57 million versus $0.72 million using classification 1). Both types of funds are generally open to new investments (91% of the funds) and they both allow investors to make subscriptions roughly every 30 to 34 days. About 64% and 61% (using classification 1) of quantitative and qualitative funds have US addresses. The average firm size of quantitative funds is substantially larger ($20 billion versus $8 billion using classification 1). This might reflect the economies of scale inherent in launching other quantitative hedge funds within the same firm with a similar quantitative process. On the whole, qualitative funds look more illiquid, in the sense that the average redemption period is longer, the amount of advanced notice a hedge fund needs for withdrawals is longer, and that they have on average almost double the lockup period (123 days versus 52 days using classification 1).[14] Quantitative hedge funds seem to be less transparent on average than qualitative funds. In our sample, 32% are SEC registered compared to 46% of the qualitative funds using classification 1. This might be due to the sensitive nature of proprietary models.

Table 6 is the final table that we present on the management differences between quantitative and qualitative funds. The percentage of funds that use leverage is roughly equivalent at 74% and 76%.[15] The types of legal structure are very similar, with limited partnerships (L.P.) and limited liability companies (L.L.C.) being the most common. On the whole, quantitative funds tend to invest less in North America than qualitative funds. Macro Currency funds have almost zero investments in North America both for qualitative and quantitative funds.[16]

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[11] This is visible in Figure 1 where the assets at the start of January 1994 are normalised to be same for the two types of management styles.

[12] High water marks are defined by a ‘yes’ or ‘no’ in the database.

[13] The database contains all sorts of hurdle rates, such as 6-month LIBOR or the 3-month Treasury bill rate, thus we count the funds by looking at those that have no hurdle rate.

[14] The database contains various entries for subscription, including ‘Anytime’, ‘Semi-Annual’, thus we converted each of these into a number of days. The same is true for redemptions, which are given values such as ‘1 year’, ‘Annually’, ‘18 Month’, etc. Thus we converted these into number of day equivalents as well. Lockup was also given in text format, such as ‘1 Quarter’, ‘1 Day’, etc. and we converted these to a number of days format.

[15] There were various text responses to leverage in the database, including the specification of the amount of leverage. We simply counted the ones that had an entry of no leverage.

[16] Not all funds reported for this category. Thus, amongst the funds that had a response we computed the percentages invested in various regions. Europe contained several categories,

Table 5

Characteristics of quantitative and qualitative hedge funds II

This table reports the average of the fund characteristics as of June 2009. C1 refers to classification 1 for quantitative and qualitative funds, while C2 refers to classification 2. Minimum Invest. reports the average minimum investment required, subscription reports the average frequency that investors are allowed to make subscriptions, Open for Investment reports the percentage of hedge funds that are open for new investments, Country located is the percentage of hedge funds with a US address, Firm Size is the average size of the entire firm in billions of US dollars, Redemption reports the average frequency in number of days for redemption, Advance Notice reports the average number of days the hedge fund requires for notice to withdraw funds, Lockup reports the average number of days that investor funds cannot be withdrawn, SEC registered reports the percentage of hedge funds that are registered with the SEC.

	Investability					Liquidity			Transparency
Group	Minimum Invest. (Mil.)	Subscription	Open for Investment	Country Located	Firm Size (Bil.)	Redemption.	Advance. Notice	Lockup	SEC Registered
Quantitative (C1)	1.57	29.56	0.91	64.17	20.16	42.19	21.17	52.08	31.55
Qualitative (C1)	0.72	33.95	0.91	61.45	7.55	68.21	33.85	122.58	46.35
Quantitative (C2)	1.36	29.89	0.94	70.48	18.58	52.38	29.45	79.23	42.21
Qualitative (C2)	1.02	34.07	0.90	66.52	9.39	70.29	36.47	117.17	44.40
Quant. Sub. (C1)									
EH:EqMktNeu	1.33	32.42	0.91	60.17	46.13	46.32	27.07	74.41	48.52
EH:QuantDir	1.37	39.87	0.93	75.34	4.02	77.17	31.04	113.92	32.77
M:CmdtySys	0.45	22.41	1.00	43.66	1.58	24.10	11.01	7.03	19.72
M:CrrcySystm	2.82	22.64	0.90	55.28	29.57	26.74	14.00	14.19	21.12
M:SysDivrsf'd	1.66	24.17	0.88	66.67	4.70	26.83	13.57	15.05	21.60
Qual. Sub. (C1)									
EH:FndmtlGr	0.53	32.57	0.91	54.45	5.89	63.39	34.58	113.56	43.87
EH:FndmtlVal	0.73	35.97	0.91	65.89	8.19	76.13	34.96	142.15	50.79
M:CmdtyDiscr	0.27	27.22	0.78	44.44	13.19	33.89	25.67	26.76	16.67
M:CrrcyDiscr	5.03	17.16	1.00	63.16	9.22	17.26	17.58	0.00	31.58
M:DscrThm	0.92	29.81	0.91	60.63	8.58	49.82	28.31	70.21	35.19

Table 6

Characteristics of quantitative and qualitative hedge funds III

This table reports the average of the fund characteristics as of June 2009. C1 refers to classification 1 for quantitative and qualitative funds, while C2 refers to classification 2. Leverage reports the percentage of funds that use leverage, Legal reports the percentage of firms set up as various legal entities, including limited partnerships (L.P.), L.L.C. (limited liability companies), corporations (Corp.), and other, which represented all other forms of legal entities. Regional Investment Focus reports the percentage of firms that focus on investing in a particular region, including North America, Latin America, Asia, Europe, and Other.

		Legal structure							Regional Investment Focus				
Group	Leverage	L.P.	Corp.	L.L.C.	M.A.	I.C.	U.T.	Other	North America	Latin America	Asia	Europe	Other
Quantitative (C1)	73.99	25.31	12.22	17.76	6.30	3.46	16.44	18.51	28.35	0.65	5.52	9.74	55.74
Qualitative (C1)	76.07	36.78	10.59	21.22	8.46	4.52	0.94	17.49	36.21	1.24	19.38	20.90	22.20
Quantitative (C2)	74.42	34.23	14.33	17.12	7.21	5.19	9.13	12.79	40.64	0.37	5.17	8.25	45.44
Qualitative (C2)	75.44	34.07	11.15	21.28	7.83	3.70	4.25	17.72	41.74	1.50	12.13	14.45	30.09
Quant. Sub. (C1)													
EH:EqMktNeu	68.64	29.66	12.29	17.16	9.96	6.78	4.03	20.13	43.71	0.63	12.26	21.07	22.33
EH:QuantDir	67.91	46.28	8.45	18.58	3.72	1.35	7.43	14.19	59.20	2.40	6.40	13.60	18.40
M:CmdtySys	60.56	18.31	16.90	35.21	7.04	0.00	7.04	15.49	9.86	0.00	1.41	2.82	85.92
M:CrrcySystm	86.34	6.83	9.94	19.88	6.83	1.86	37.89	16.77	1.04	0.00	1.04	0.00	97.92
M:SysDivrsf'd	79.59	17.18	14.12	15.14	4.42	2.72	26.19	20.24	13.06	0.32	0.64	1.27	84.71
Qual. Sub. (C1)													
EH:FndmtlGr	74.71	30.71	7.61	25.03	7.23	4.90	0.00	24.52	24.31	3.14	35.49	21.37	15.69
EH:FndmtlVal	75.02	43.23	11.67	17.58	8.90	4.11	0.52	13.99	47.47	0.39	14.88	24.81	12.35
M:CmdtyDiscr	66.67	11.11	22.22	22.22	22.22	0.00	11.11	11.11	22.22	0.00	0.00	5.56	72.22
M:CrrcyDiscr	84.21	5.26	15.79	10.53	21.05	0.00	36.84	10.53	0.00	0.00	0.00	0.00	100.00
M:DscrThm	84.67	26.83	12.54	28.57	8.01	5.92	2.44	15.68	12.82	1.03	4.62	2.56	78.97

Overall, despite some minor differences, the management characteristics of quantitative and qualitative funds do not seem to be altogether different.

4. Performance Differences

In order to examine the performance differences of quantitative and qualitative hedge funds, we must use performance metrics. In this paper, in addition to standard return and risk measures as well as risk-adjusted measures, we also examine excess performance measures after accounting for some type of asset-pricing model.

In order to measure risk-adjusted performance, we use a similar model to the one in Fung and Hsieh (2004). The model estimated is:

$$\begin{aligned}\tilde{r}_{it} = \alpha_{iT} &+ \beta_{1iT}\text{RMRF} + \beta_{2iT}\text{SMB} + \beta_{3iT}\text{HML} + \beta_{4iT}\text{MOM} \\ &+ \beta_{5iT}\,10\text{yr} + \beta_{6iT}\text{CS} + \beta_{7iT}\text{BdOpt} + \beta_{8iT}\text{FXOpt} \\ &+ \beta_{9iT}\text{ComOpt} + \beta_{10iT}\text{EE} + \varepsilon_{it} \quad t = 1, 2, \ldots T\end{aligned} \tag{1}$$

where $\tilde{r}_{it} (= r_{it} - r_{ft})$ is the net-of-fee return on a hedge fund portfolio in excess of the risk-free rate, RMRF is the excess return on a value-weighted aggregate market proxy, SMB, HML, and MOM are the returns on a value-weighted, zero-investment, factor-mimicking portfolio for size, book-to-market equity, and one-year momentum in stock returns as computed by Fama and French,[17] 10yr is the Lehman US Treasury 10-year bellwether total return, CS is the Lehman aggregate intermediate BAA corporate bond index return minus the Lehman US Treasury 10-year bond return, BdOpt is the lookback straddle for bonds,[18] FXOpt is the lookback straddle for foreign exchange, ComOpt is the lookback straddle for commodities, and EE is the total return from an emerging market equity index.[19] These models are typically employed to extract the stock picking skill of the portfolio manager or has Henrikson and Merton like to call security analysis or the microforecasting ability of the portfolio manager.

For the tests of market timing, the above model is modified to include a term that captures the market timing ability (or macroforecasting skills) of the portfolio manager.

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including Northern Europe, Pan-European, Russia/Eastern Europe, Western Europe/UK. Asia contained several categories including Asia ex-Japan, Asia w/ Japan, and Japan. The Other category included Pan-American, Africa, Global, Middle East, and Multiple Emerging Markets.

[17] Source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[18] The lookback straddle data was obtained from http://faculty.fuqua.duke.edu/dah7/DataLibrary/TF-FAC.xls. The lookback straddle is a derivative security that pays the holder the difference of the maximum and minimum prices of the underlying asset over a given time period. For more information on the calculation of these straddles, please see Fung and Hsieh (2001, 2004).

[19] This factor was added to the standard Fung-Hsieh factors after speaking with David Hsieh who suggested that this factor is important.

$$\begin{aligned}\tilde{r}_{it} = \alpha_{iT} + \beta_{1iT}\mathrm{RMRF} + \beta_{2iT}\mathrm{SMB} + \beta_{3iT}\mathrm{HML} + \beta_{4iT}\mathrm{MOM} \\ + \beta_{5iT}\,10\mathrm{yr} + \beta_{6iT}\mathrm{CS} + \beta_{7iT}\mathrm{BdOpt} + \beta_{8iT}\mathrm{FXOpt} \\ + \beta_{9iT}\mathrm{ComOpt} + \beta_{10iT}\mathrm{EE} + \gamma_{iT}\mathrm{TIMING} + \varepsilon_{it} \quad t = 1, 2, \ldots T\end{aligned} \tag{2}$$

where TIMING is the standard measure of market timing, $\max(0, -[r_{M,t} - r_{f,t}])$ (Henrikson and Merton, 1981). Focusing on the first equation, which is a standard CAPM test with a TIMING variable, a perfect market timer should have a $\beta = 1$ and a $\gamma = 1$. This would imply an equity portfolio manager that is 100% invested in equities, however in any month where the return of the market is less than the risk-free rate, the manager will sell the entire portfolio and put the securities in cash.[20] In reality, it will be rare for hedge fund managers to engage in such an extreme market timing procedure, however Merton (1981) shows that as long as the timer has greater than random accuracy in predicting up and down markets and that he alters beta accordingly in up and down markets, then γ will be positive and significant. Thus, a test for a positive and significant γ is sufficient to determine market timing ability. All of our measurement periods of performance are from January 1994 to March 2009 unless otherwise indicated.

4.1. *Raw performance*

Table 7 shows performance summary statistics for the quantitative and qualitative funds using classification method 1 and classification method 2. Generally, quantitative funds have a higher average return and a lower average standard deviation than qualitative funds using classification 1, however using classification 2, the reverse is true. Amongst the quantitative funds, the highest average return comes from the Quantitative Directional strategy. The correlations of the fund categories with the S&P 500 are quite low at 0.17 and 0.38 for quantitative and qualitative respectively. The risk-adjusted return measures provide mixed evidence, but overall seem to favour quantitative funds. The average Sharpe and Omega ratio are higher for the qualitative category, while the Sortino, Calmar, and Sterling ratios are higher for the quantitative category.[21]

Table 8 shows the performance of the quantitative and qualitative funds in other sub-periods, as well as in up and down markets using classification method 1 and 2. The qualitative funds perform significantly better than quantitative funds in up markets (25% and 15% respectively). However, the quantitative funds do significantly better in down markets (-2% versus -16%) using classification 1. This is mainly driven by the presence of Equity Market Neutral funds. A similar qualitative result is found using classification 2. In the 1990s, the average qualitative fund return was higher than the average quantitative fund return.[22] They were roughly the same from 2000 to 2009 for classification 1, while quantitative funds did better using classification 2. During the financial crisis (which we measure from January 2007 to March 2009), quantitative funds did better than qualitative funds (3.29% versus -4.77%) using classification 1 and also better (1.41% versus

[20] In theory, the portfolio manager does not need to liquidate the entire portfolio, they could simply engage in a position that effectively changes the β from 1 to 0.

[21] These risk-adjusted measures are explained in more detail in Appendix A.

[22] The 1990s returns were computed only from 1994 to 1999 due to the survivorship bias with hedge fund databases explained in a prior section.

Table 7

Quantitative and qualitative hedge fund performance summary statistics I

This table reports the averages across all hedge funds for various statistics from January 1994 to March 2009. C1 refers to classification 1 for quantitative and qualitative funds, while C2 refers to classification 2. Mean is the average return of all the individual hedge funds' average monthly returns annualised by multiplying by 12. S.D. is the average standard deviation of the individual hedge funds' standard deviations of returns over the period annualised by multiplying by $\sqrt{12}$. Max. and Min. are the maximum (minimum) monthly return of any hedge fund over the period. ρ represents the correlation of the averaged series over time with the S&P 500 returns. The Risk-Adjusted measures are the Sharpe ratio, Sharpe $= \frac{\bar{r}_{it}-\bar{r}_{ft}}{\sigma_i}$, the Sortino ratio, Sortino $= \frac{\bar{r}_{it}-\bar{r}_{ft}}{\sqrt{LPM_{2i}(\bar{r}_{it})}}$, and the Omega ratio, Omega $= \frac{\bar{r}_{it}-\bar{r}_{ft}}{LPM_{1i}(\bar{r}_{it})} + 1$, where $LPM_{ni}(\tau) = \frac{1}{T}\sum_{i=1}^{T}\left[\max\left(\tau - r_{it}, 0\right)\right]^n$. The latter two are similar to the Sharpe ratio but use downside-risk measures rather than variance. The Calmar ratio is given by Calmar $= \frac{\bar{r}_{it}-\bar{r}_{ft}}{-MD_{i1}}$, and the Sterling ratio is given by Sterling $= \frac{\bar{r}_{it}-\bar{r}_{ft}}{\sum_{j=1}^{N} -\mathrm{MD}_{ij}}$, where MD_{i1} is the maximum drawdown of the fund from peak to trough during the existence of the fund in percentage terms, MD_{i2} is the next largest drawdown of the fund in percentage terms, and so on. In the case of the Sterling measure, we take $N=4$ to represent the four largest drawdowns for the fund during the period of concern. The drawdowns are computed by creating an index series of the fund based upon net returns. S&P 500 total return data and the 10-year Treasury bond total return data were obtained from Global Financial Data.

						Risk-adjusted return measures				
Group	Mean	S.D.	Max.	Min.	ρ	Sharpe	Sortino	Omega	Calmar	Sterling
Quantitative (C1)	9.80	15.71	241.32	−90.78	0.17	0.42	0.19	1.33	5.84	8.01
Qualitative (C1)	8.90	16.71	172.20	−86.60	0.38	0.43	0.19	1.34	4.08	5.77
Quantitative (C2)	8.53	13.14	130.88	−69.62	0.18	0.51	0.22	1.40	7.87	12.60
Qualitative (C2)	8.96	15.11	241.32	−97.50	0.30	0.58	0.26	1.47	5.42	8.43
Quant. Sub. (C1)										
EH:EqMktNeu	6.04	8.11	36.16	−30.45	0.11	0.39	0.17	1.31	5.14	8.60
EH:QuantDir	11.91	21.45	241.32	−90.78	0.46	0.42	0.18	1.33	6.36	7.74
M:CmdtySys	9.47	18.77	94.99	−38.56	0.09	0.37	0.16	1.29	4.36	5.34
M:CrrcySystm	8.96	13.23	114.00	−32.59	0.04	0.28	0.14	1.21	4.91	6.29
M:SysDivrsf'd	10.95	17.33	81.00	−54.50	0.02	0.43	0.19	1.33	6.04	7.90
Qual. Sub. (C1)										
EH:FndmtlGr	9.45	21.15	172.20	−77.50	0.43	0.38	0.17	1.31	2.51	3.08
EH:FndmtlVal	8.50	14.56	97.61	−60.80	0.39	0.45	0.20	1.36	4.84	7.29
M:CmdtyDiscr	11.83	13.48	67.27	−33.59	0.00	0.69	0.32	1.57	6.72	8.43
M:CrrcyDiscr	9.83	10.08	63.23	−26.77	0.07	0.58	0.28	1.49	3.78	4.43
M:DscrThm	9.03	15.36	106.51	−86.60	0.21	0.42	0.18	1.34	4.32	5.30
S&P 500 Index	6.61	15.44	9.78	−16.79	1.00	0.19	0.07	1.14	0.24	0.24
Bond Index	7.03	7.40	9.02	−6.71	−0.06	0.45	0.19	1.34	3.37	3.60

−3.29%) using classification 2. The examination of the returns of both quantitative and qualitative funds indicates that although the returns are not much more skewed than the normal distribution, they have much more kurtosis. The main difference between quantitative and qualitative funds along this dimension is that qualitative macro funds have returns that deviate much more from the normal distribution.

Table 8

Quantitative and qualitative hedge fund performance summary statistics II

This table reports the average returns of individual fund returns over the entire sample period from January 1994 to March 2009. C1 refers to classification 1 for quantitative and qualitative funds, while C2 refers to classification 2. Mean is the average return of all the individual hedge funds' average monthly returns annualised by multiplying by 12. Skewness is a measure of skewness of the sample distribution of fund returns, Kurtosis is a measure of kurtosis of the sample distribution, and Jarque-Bera reports the average Jarque-Bera test statistic for the normality of the fund returns across hedge funds.

	Mean returns					Non-normality		
	Up	Down	90-00	00-09	07-09	Skewness	Kurtosis	Jacque-Bera
Quantitative (C1)	15.26	−1.72	15.93	5.90	3.29	0.04	4.86	62.69
Qualitative (C1)	24.51	−16.25	26.63	5.90	−4.77	−0.19	5.53	118.83
Quantitative (C2)	15.06	−1.84	17.95	6.93	1.41	−0.18	6.01	264.66
Qualitative (C2)	20.26	−9.79	21.16	5.94	−3.29	−0.28	6.63	260.93
Quant. Sub. (C1)								
EH:EqMktNeu	8.41	2.08	12.70	4.93	1.12	−0.24	5.19	76.01
EH:QuantDir	32.72	−28.82	21.52	1.23	−5.32	−0.11	4.99	83.82
M:CmdtySys	14.14	2.17	9.52	9.37	2.28	0.05	4.51	38.82
M:CrrcySystm	9.75	7.08	11.51	7.15	1.77	0.42	5.27	77.23
M:SysDivrsf'd	13.63	5.99	15.67	8.08	9.58	0.24	4.46	40.22
Qual. Sub. (C1)								
EH:FndmtlGr	31.11	−25.66	26.98	5.04	−7.26	−0.24	5.55	160.38
EH:FndmtlVal	22.61	−13.79	28.61	6.00	−5.27	−0.21	5.40	75.87
M:CmdtyDiscr	11.19	12.57	13.34	11.97	10.22	0.71	8.63	1018.14
M:CrrcyDiscr	10.46	8.64	25.11	8.28	4.84	0.19	8.69	548.24
M:DscrThm	17.29	−5.75	17.23	7.17	2.04	−0.05	5.72	121.78
S&P 500 Index	38.89	−47.99	22.25	−3.54	−21.18	−0.69	3.95	21.08
Bond Index	6.32	8.23	5.68	7.91	11.28	0.17	4.23	12.27

Although the preliminary investigation of the returns of quantitative and qualitative funds suggests no clear consensus on which group performs better, this analysis has not controlled for the risks of these funds. For example, Equity Market Neutral funds have substantially different risk profiles than Fundamental Growth funds. We attempt to control for this in the next section.

4.2. *Risk-adjusted performance*

In this section, we analyse the performance of quantitative and qualitative funds using both classification methods 1 and 2. We do this by computing individual risk-adjusted regressions on quantitative and qualitative funds, as well as pooled regressions, where we comingle both types of funds and introduce a dummy variable with a value of 1 for quantitative funds and a value of 0 for qualitative funds. The coefficient on the variable, δ, represents the amount to add or subtract from α to get the total value of α for quantitative funds as compared to qualitative funds. Thus, a positive value of δ indicates that quantitative funds outperform qualitative funds on a risk-adjusted basis.

Table 9 contains the risk-adjusted return measures from the models discussed earlier in Section 4. Columns (1) - (5) contain the results using classification method 1 to separate quantitative and qualitative hedge funds. Columns (1) - (2) represent panel regressions on quantitative funds using the 10-factor Fama-French model with Fung-Hsieh factors and emerging equities (henceforth denoted as the 10-factor model), and the 10-factor model controlling for fixed sub-strategy effects and yearly time effects. Columns (3) - (4) do the same but for a panel of qualitative funds. Columns (5) and (6) present the panel regressions including both quantitative and qualitative funds with a 10-factor model with interaction dummies on the parameters and a dummy (δ) for whether the fund is quantitative or qualitative. This allows for a pooling of the hedge fund data. Column (5) presents the regression results using classification 1 and column (6) present the results using classification 2.

Columns (7) - (10) contain results for classification 2 and the tests are run within each major hedge fund category: Equity Hedge (Column 7), Macro (Column 8), Event Driven (Column 9), and Relative Value (Column 10). In all cases, a dummy for quantitative funds is included in the regressions with coefficient δ.

Columns (1) and (2) indicate that quantitative funds have large and significant αs even when using a 10-factor model. Column (1) reports an α of 0.32 which is equivalent to 0.32% per month or 3.84% per year. The qualitative funds also have positive and significant αs, although generally smaller than the quantitative funds.

Columns (5) and (6) report the pooled regression results. The important coefficient is the coefficient on δ which reports the amount to add or subtract from α to get the true α of quantitative funds versus qualitative funds. In Column (5), the $\hat{\delta}$ is 0.06 and $\hat{\delta}$ is indeed positive and significant. In fact, in this specification, we find that the $\hat{\alpha}$ is 0.26%, with $\hat{\delta} = 0.06$. Thus, quantitative funds have an α that is 6 bps higher per month than qualitative funds after accounting for fees. This result is similar when the quantitative and qualitative funds are divided according to classification method 2 (see Column (6)).

The results hold within main hedge fund categories where quantitative and qualitative are separated within each category by their fund descriptions (Columns (7) to (10)). For all categories, the $\hat{\delta}$ is positive and it is statistically significant for the Macro and Relative Value categories. The evidence presented for our hedge fund sample over the period 1994 to 2009 suggests that quantitative funds as a group outperformed qualitative funds on a risk-adjusted basis.

4.3. *Market timing*

In this section, we investigate the difference in market timing ability between quantitative and qualitative funds. We implement the same regressions as before with a Henrikkson-Merton timing variable included as discussed in Section 4. The results are presented in Table 10. Columns (1) to (2) show a positive and significant timing coefficient ($\gamma_{Timing} > 0$) for the pooled group of hedge funds. Quantitative funds are even more successful at timing as shown by the interaction term ($\gamma_{Quant \times Timing} > 0$). This result is in agreement with that found in Kazemi and Li (2009) that systemic CTAs have better timing ability than discretionary CTAs. Although there is mixed evidence about market timing for hedge funds based on the methodology used (Eling, 2009), our results about positive market timing have also been confirmed using separation techniques by Ammann *et al.*

Table 9

Differences in alpha performance of quantitative and qualitative individual hedge funds

This table reports the pooled regressions of the hedge fund returns from January 1994 to March 2009. Columns (1) - (5) contain the results using classification 1 to separate quantitative and qualitative hedge funds, while columns (6) - (10) contain the results using classification 2. Columns (1) and (2) are the averages of the parameters from individual hedge fund regressions on quantitative funds, columns (3) and (4) are the averages of individual hedge fund regressions for qualitative funds, columns (5) and (6) are pooled regressions with quantitative and qualitative funds, and columns (7) to (10) are the averages of the parameters from individual hedge fund regressions on specific hedge fund categories using classification 2. The hedge fund categories are equity hedge, macro, event driven, and relative value respectively. The results are from the following ordinary least squares (OLS) regressions with standard errors corrected by the Newey and West (1987) procedure with three lags: $\tilde{r}_{it} = \alpha + \sum_{j=1}^{K} \beta_j r_{jt} + \lambda_t + \theta_s + \delta Z_i + \varepsilon_t$, where $\tilde{r}_{it}$ is the net-of-fee return from $t-1$ to t of fund i minus the risk-free rate, $K = 10$ for the 10-factor model, λ_t is a series of dummies to control for time effects, θ_s is a set of dummies to control for fixed effects between hedge fund sub-categories, Z_i is a dummy variable which takes a value of 1 if the hedge fund is a quantitative hedge fund and 0 otherwise, and ε_{it} is the residual. Both θ_s and Z_i are not used in the same regression so as to avoid perfect multicollinearity. Thus regression with strategy effects do not naturally have the quantitative dummy (Stock and Watson, 2007; Wooldridge, 2009). Time Effects = 0 presents F-tests and p-values for whether yearly time effects are 0, and Fixed Effects = 0 presents F-tests and p-values for whether sub-category fixed effects are 0 or not. For Columns (5) - (10), the Time Effects and Fixed Effects entries represent F-tests and p-values for whether the constant and other interaction terms are significantly different from 0 or whether just the interaction terms are significantly different from 0 respectively. Average *t*-statistics are listed directly under the average parameter estimates. α and δ estimates are multiplied by 100.

Indep. variables	Classification 1						Classification 2			
	Quantitative		Qualitative		Both		Main strategy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
α	0.32	0.25	0.26	0.14	0.26	0.26	0.29	0.32	0.31	0.09
	16.36	2.87	15.85	1.46	15.85	23.42	17.95	11.42	13.53	4.48
δ	.	.	.	.	0.06	0.06	0	0.1	0.01	0.14
	.	.	.	.	2.18	2.52	0.03	2.18	0.07	2.85
β_{RMRF}	0.09	0.05	0.24	0.23	0.24	0.18	0.29	−0.03	0.15	0.04
	13.43	6.89	42.35	35.67	42.35	47.61	50.29	−3.56	19.61	6.87
β_{SMB}	0.02	0.03	0.04	0.05	0.04	0.03	0.04	0.01	0.07	0.01
	3.98	4.35	7.04	8.49	7.04	9.4	7.13	1.39	11.51	2.30
β_{HML}	0.02	−0.01	0.02	−0.01	0.02	0.02	−0.01	0.04	0.08	0.05
	2.22	−1.58	2.95	−0.97	2.95	4.19	−2.44	5	11.03	7.32

Table 9

Continued

Indep. variables	Classification 1						Classification 2			
	Quantitative		Qualitative		Both		Main strategy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β_{MOM}	0.09	0.09	0.11	0.1	0.11	0.09	0.12	0.08	0.03	0.04
	19.1	17.79	27.11	24.84	27.1	31.52	26.44	14.78	6.86	11.01
β_{10yr}	0.17	0.13	0.1	0.07	0.1	0.21	0.11	0.31	0.23	0.39
	10.48	8	7.96	5.48	7.96	22.06	8.39	12.19	12.06	17.75
β_{CS}	0.13	0.07	0.27	0.17	0.27	0.4	0.28	0.29	0.52	0.74
	5.22	2.92	13.52	8.18	13.52	27.7	14.46	7.47	17.42	21.31
β_{BdOpt}	0.02	0.02	0	0	0	0	0	0.03	−0.01	−0.00
	14.61	12.56	1.44	−1.82	1.44	5.58	1.63	13.66	−7	−1.73
β_{FXOpt}	0.02	0.02	0.01	0.01	0.01	0.01	0	0.03	0.01	−0.00
	23.16	22.91	8.86	8.26	8.86	17.92	7.39	22.3	6.11	−2.32
β_{ComOpt}	0.02	0.02	0	0	0	0	0	0.03	−0.01	−0.01
	12.72	15.39	−2.06	1.74	−2.06	1.29	−4.31	17.23	−4.33	−5.43
β_{EE}	0.08	0.11	0.2	0.21	0.2	0.13	0.17	0.13	0.07	0.05
	21.51	25.93	55.73	56.95	55.73	57.46	49.56	24.3	14.02	13.04
$\beta_{Quant \times RMRF}$	.	.	.	.	−0.16	−0.1	−0.09	−0.04	0.09	−0.03
	.	.	.	.	−18.04	−12.32	−6.99	−2.86	2.14	−1.81
$\beta_{Quant \times SMB}$	.	.	.	.	−0.01	−0.03	−0.03	−0.01	0.02	−0.01
	.	.	.	.	−1.67	−3.37	−2.13	−0.93	0.71	−1.20
$\beta_{Quant \times HML}$	.	.	.	.	0	0.03	0.05	0.01	−0.04	−0.02
	.	.	.	.	−0.18	3.06	3.81	0.35	−0.87	−1.43
$\beta_{Quant \times MOM}$	.	.	.	.	−0.02	0	−0.01	0	0.04	−0.01
	.	.	.	.	−2.79	−0.43	−0.81	−0.01	1.07	−1.39
$\beta_{Quant \times 10yr}$	.	.	.	.	0.06	−0.06	−0.07	−0.14	0.01	−0.01
	.	.	.	.	3.11	−2.86	−2.7	−3.48	0.09	−0.15
$\beta_{Quant \times CS}$	.	.	.	.	−0.14	−0.15	−0.14	−0.17	0	−0.00
	.	.	.	.	−4.59	−5.04	−3.59	−2.97	0.02	−0.04

Table 9
Continued

Indep. variables	Classification 1						Classification 2			
	Quantitative		Qualitative		Both		Main strategy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\beta_{Quant \times BdOpt}$	.	.	.	.	0.02	0.01	0	0	0.01	0.00
	.	.	.	.	10.26	4.87	0.26	0.37	1.51	0.65
$\beta_{Quant \times FXOpt}$	.	.	.	.	0.02	0.01	0	0	0.01	0.00
	.	.	.	.	13.95	5.64	0.02	0.37	1.22	0.91
$\beta_{Quant \times ComOpt}$	.	.	.	.	0.02	0	0	−0.01	0	0.00
	.	.	.	.	11.58	3.55	0.8	−1.91	−0.32	1.06
$\beta_{Quant \times EE}$	.	.	.	.	−0.12	−0.05	−0.09	−0.02	0.03	−0.01
	.	.	.	.	−22.53	−9.42	−12.32	−2.31	1.39	−1.37
N	121911	121911	192478	192478	314389	489594	257023	91434	51905	82460
$\overline{R}^2$	0.04	0.05	0.19	0.19	0.14	0.1	0.16	0.06	0.15	0.11
Newey w/ 3 Lags	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy Control?	No	Yes	No	Yes	No	No	No	No	No	No
Year Controls?	No	Yes	No	Yes	No	No	No	No	No	No
Main HF							EH	M	ED	RV
F-stats and p-values testing exclusion of groups of variables										
Time Effects = 0	.	26.83	.	66.96	312.58	93.73	65.61	6.65	1.66	1.79
	.	0	.	0	0	0	0	0	0.08	0.05
Fixed Effects = 0	.	35.24	.	5.49	322.7	96.17	66.23	7.26	1.82	1.73
	.	0	.	0	0	0	0	0	0.05	0.07

Table 10

Differences in timing ability between quantitative and qualitative hedge funds

This table reports the pooled regressions of the hedge fund returns from January 1994 to March 2009. Columns (1) contains the results using classification 1 to separate quantitative and qualitative hedge funds, while columns (2) - (6) contain the results using classification 2. Columns (3) to (6) represent the results within a hedge fund category, where the hedge fund categories are equity hedge, macro, event driven, and relative value respectively. The results are from the following ordinary least squares (OLS) regressions with standard errors corrected by the Newey and West (1987) procedure with three lags: $\tilde{r}_{it} = \alpha + \sum_{j=1}^{K} \beta_j r_{jt} + \lambda_t + \theta_s + \gamma_{Timing} W + \delta Z_i + \varepsilon_t$, where $\tilde{r}_{it}$ is the net-of-fee return from $t-1$ to t of fund i minus the risk-free rate, $K = 10$ for the 10-factor model, λ_t is a series of dummies to control for time effects, θ_s is a set of dummies to control for fixed effects between hedge fund sub-categories, Z_i is a dummy variable which takes a value of 1 if the hedge fund is a qualitative hedge fund and 0 otherwise, γ_{Timing} represents the timing factor coefficient, where W equals $\max(0, -[r_{M,t} - r_{f,t}])$ for the Henrikson-Merton model, and ε_{it} is the residual. Both θ_s and Z_i are not used in the same regression so as to avoid perfect multicollinearity. Thus regression with strategy effects do not naturally have the quant dummy. Time Effects = 0 presents F-tests and p-values for whether decade time effects are 0, and Fixed Effects = 0 presents F-tests and p-values for whether sub-category fixed effects are 0 or not. For Columns (2) - (6), the Time Effects and Fixed Effects entries represent F-tests and p-values for whether the constant and other interaction terms are significantly different from 0 or whether just the interaction terms are significantly different from 0 respectively. Average t-statistics are listed directly under the average parameter estimates. α and δ estimates are multiplied by 100.

Indep. variables	Both		Main strategy			
	(1)	(2)	(3)	(4)	(5)	(6)
α	−0.03	0.06	0.04	−0.19	0.37	0.16
	−1.29	4.04	1.94	−4.71	12.88	6.38
δ	−0.09	−0.12	−0.05	−0.03	0.02	−0.04
	−2.56	−3.68	−1.17	−0.39	0.1	−0.74
γ_{Timing}	0.15	0.11	0.13	0.27	−0.04	−0.04
	12.54	12.87	10.89	12.96	−2.37	−2.60
$\gamma_{Quant \times Timing}$	0.08	0.09	0.03	0.06	0	0.10
	4.07	5.4	1.17	1.85	−0.02	3.01
β_{RMRF}	0.33	0.24	0.36	0.12	0.13	0.02
	37.79	40.94	41.54	8.43	11.22	2.25
β_{SMB}	0.04	0.03	0.04	0.02	0.07	0.01
	7.67	10.05	7.64	2.14	11.4	2.14
β_{HML}	0.03	0.02	−0.01	0.06	0.08	0.04

Table 10
Continued

Indep. variables	Both		Main strategy			
	(1)	(2)	(3)	(4)	(5)	(6)
	4.78	5.98	−0.97	7.02	10.67	7.13
β_{MOM}	0.11	0.09	0.12	0.08	0.03	0.04
	27.46	31.82	26.64	15.31	6.77	10.98
β_{10yr}	0.13	0.22	0.13	0.35	0.22	0.39
	10.42	24.79	10.5	14.33	12.22	18.34
β_{CS}	0.32	0.43	0.32	0.37	0.51	0.73
	16.3	30.9	16.9	9.99	17.87	22.09
β_{BdOpt}	0	0	0	0.03	−0.01	−0.00
	0.09	4.16	0.32	12.37	−6.84	−1.41
β_{FXOpt}	0.01	0.01	0	0.03	0.01	−0.00
	8.07	17.13	6.72	21.6	6.24	−2.15
β_{ComOpt}	0	0	0	0.03	−0.01	−0.01
	−1.57	1.78	−3.89	17.66	−4.42	−5.48
β_{EE}	0.2	0.13	0.18	0.14	0.07	0.05
	57.14	59.16	50.85	25.72	13.96	12.95
$\beta_{Quant\times RMRF}$	−0.12	−0.05	−0.07	0	0.09	0.03
	−8.73	−3.83	−3.73	−0.16	1.29	1.48
$\beta_{Quant\times SMB}$	−0.01	−0.02	−0.03	−0.01	0.02	−0.01
	−1.45	−3.08	−2.09	−0.77	0.69	−1.02
$\beta_{Quant\times HML}$	0	0.03	0.05	0.01	−0.04	−0.01
	0.31	4.05	4.06	0.9	−0.94	−0.97
$\beta_{Quant\times MOM}$	−0.02	0	−0.01	0	0.04	−0.01
	−2.72	−0.12	−0.7	0.2	1.06	−1.24
$\beta_{Quant\times 10yr}$	0.07	−0.04	−0.06	−0.12	0.01	0.01
	3.71	−1.93	−2.47	−3.1	0.08	0.23
$\beta_{Quant\times CS}$	−0.12	−0.12	−0.13	−0.15	0	0.03
	−3.97	−4.23	−3.45	−2.76	0.01	0.37
$\beta_{Quant\times BdOpt}$	0.02	0.01	0	0	0.01	0.00

Table 10
Continued

Indep. variables	Both		Main strategy			
	(1)	(2)	(3)	(4)	(5)	(6)
	9.87	4.6	0.33	0.36	1.53	0.36
$\beta_{Quant \times FXOpt}$	0.02	0.01	0	0	0.01	0.00
	13.69	5.28	−0.09	0.24	1.23	0.67
$\beta_{Quant \times ComOpt}$	0.02	0.01	0	−0.01	0	0.00
	11.78	3.72	0.81	−1.84	−0.32	1.14
$\beta_{Quant \times EE}$	−0.12	−0.04	−0.09	−0.02	0.03	−0.01
	−22.38	−9.01	−12.34	−2.14	1.4	−1.04
N	314389	489594	257023	91434	51905	82460
$\overline{R}^2$	0.14	0.11	0.17	0.06	0.15	0.11
Newey w/ 3 Lags	Yes	Yes	Yes	Yes	Yes	Yes
Strategy Control?	No	No	No	No	No	No
Year Controls?	No	No	No	No	No	No
Main HF			EH	M	ED	RV
F-stats and p-values testing exclusion of groups of variables						
Time Effects = 0	296.03	86.28	61.25	5.75	1.52	1.86
	0	0	0	0	0.11	0.03
Fixed Effects = 0	310.92	89.37	63.97	6.21	1.65	1.84
	0	0	0	0	0.08	0.04

(2013). In addition to this, the $\hat{\alpha}$ of the 10-factor model for both classification method 1 and method 2 drops significantly.

This pattern continues within hedge fund categories for the equity hedge and macro funds, however event driven and relative value hedge funds appear to be poor timers.

Another very interesting result is that when the timing variable is included in the pooled regressions, the coefficient of $\hat{\delta}$ becomes negative and significant (ranging from -0.09% to -0.12%). This evidence seems to suggest that on average quantitative funds' excess performance over qualitative funds comes from the quantitative hedge funds' ability to engage in market timing of some sort. It should be noted that significance of the market timing variable may be due to the timing of other factors in their quantitative models and is being picked up by the market timing proxy. That is, it may be that some of these hedge funds are not timing the market factor, but other factors such as value versus growth, which are being captured by the market factor (see Chincarini and Nakao, 2011; Chincarini, 2012b; Bali *et al.*, 2011).

4.4. *The financial crisis of 2007–2009*

In this section we compare the performance of quantitative and qualitative funds during the financial crisis of 2008. Although the exact dates of the financial crisis may vary according to one's perspective, we chose a period that gave us sufficient observations and encapsulated the crisis. Some observers noted that the worst month of the financial crisis for quantitative funds was August 2007. Clearly, other times in 2008 were more devastating to the overall markets, including the near failure of Bear Stearns in March 2008 and the collapse of Lehman Brothers in September 2008. In order to capture enough data and all of these events, we used the period January 2007 to March 2009 as our measurement period. Table 11 contains the results of the analysis over this period. The pooled group of hedge funds have a negative alpha over the period ranging from -0.20 to -0.24 (see columns (1) and (2)). However, the dummy for quantitative funds is significantly positive and suggests that quantitative funds did somewhere between 22 to 28 bps better than qualitative funds per month during the crisis.

The evidence for the quantitative versus qualitative within categories suggests the same. The $\hat{\delta}$s are all positive, except for the relative value category.

5. Robustness

5.1. *Alternative tests*

As a further look into the issue, we performed the same analysis on equal-weighted composites of each category. That is, every month, we took all the hedge funds that were quantitative funds and took the equal-weighted average of their returns and created a monthly index for quantitative fund performance. We did a similar thing for qualitative funds and sub-strategies. We then took these indices and investigated the same performance issues.

The results were qualitatively very similar. The quantitative indices had a positive and significant $\hat{\alpha}$ that was higher than the $\hat{\alpha}$ of the qualitative funds. The $\hat{\alpha}$ in the 10-factor pooled regressions was 0.35% per month and the $\hat{\delta}$ was 0.10% per month. Thus, for the index composites the quantitative funds had higher risk-adjusted performance.

Table 11

Differences in alpha performance of quantitative and qualitative hedge funds during the financial crisis from January 2007–March 2009

This table reports the pooled regressions of the hedge fund returns from January 2007 to March 2009. Columns (1) contains the results using classification 1 to separate quantitative and qualitative hedge funds, while columns (2) - (6) contain the results using classification 2. Columns (3) to (6) represent the results within a hedge fund category, where the hedge fund categories are equity hedge, macro, event driven, and relative value respectively. The results are from the following ordinary least squares (OLS) regressions with standard errors corrected by the Newey and West (1987) procedure with three lags: $\tilde{r}_{it} = \alpha + \sum_{j=1}^{K} \beta_j r_{jt} + \lambda_t + \theta_s + \delta Z_i + \varepsilon_t$, where $\tilde{r}_{it}$ is the net-of-fee return from t - 1 to t of fund i minus the risk-free rate, $K = 10$ for the 10-factor model, λ_t is a series of dummies to control for time effects, θ_s is a set of dummies to control for fixed effects between hedge fund sub-categories, Z_i is a dummy variable which takes a value of 1 if the hedge fund is a quantitative hedge fund and 0 otherwise, and ε_{it} is the residual. Both θ_s and Z_i are not used in the same regression so as to avoid perfect multicollinearity. Thus regression with strategy effects do not naturally have the quantitative dummy. Time Effects = 0 presents F-tests and p-values for whether yearly time effects are 0, and Fixed Effects = 0 presents F-tests and p-values for whether sub-category fixed effects are 0 or not. For Columns (2) - (6), the Time Effects and Fixed Effects entries represent F-tests and p-values for whether the constant and other interaction terms are significantly different from 0 or whether just the interaction terms are significantly different from 0 respectively. Average t-statistics are listed directly under the average parameter estimates. α and δ estimates are multiplied by 100.

	Both		Main strategy			
Indep. variables	(1)	(2)	(3)	(4)	(5)	(6)
α	−0.24	−0.2	−0.24	0.04	−0.2	−0.32
	−7.91	−9.51	−8.13	0.76	−5.04	−5.93
δ	0.28	0.22	0.08	0.36	−0.03	0.16
	5.89	5.07	1.36	4	−0.14	1.54
β_{RMRF}	0.14	0.1	0.16	−0.16	0.12	0.08
	12.12	10.67	14.35	−6.24	6.1	3.28
β_{SMB}	−0.01	0	0.02	−0.23	0.09	0.07
	−0.51	−0.17	1.09	−7.46	3.9	2.37
β_{HML}	−0.07	−0.02	−0.08	0.15	0	−0.00
	−3.4	−1.73	−4.46	3.44	−0.06	−0.06
β_{MOM}	0.06	0.08	0.09	0.11	0.07	0.07
	7.82	15.29	11.36	6.87	6.63	5.13
β_{10yr}	−0.01	0.13	0.02	−0.01	0.23	0.50
	−0.4	6.24	0.71	−0.18	5.48	9.29
β_{CS}	0.18	0.33	0.21	0.14	0.48	0.77
	4.87	12.36	5.89	1.8	8.46	11.88
β_{BdOpt}	0	0	0	0.02	−0.02	−0.02
	−0.13	−1.93	−0.77	3.9	−6.25	−2.79
β_{FXOpt}	0	0	0	0	0.01	0.01
	0.88	2.31	1.19	−0.51	2.69	2.33
β_{ComOpt}	0	0	−0.01	0.04	−0.01	−0.01
	−1.14	−1.54	−3.15	7.14	−3.45	−3.11
β_{EE}	0.23	0.17	0.21	0.2	0.08	0.06
	32.32	31.9	31.94	13.62	6.55	4.30
$\beta_{Quant \times RMRF}$	−0.17	−0.04	−0.02	0.07	0.07	−0.07

Table 11
Continued

	Both		Main strategy			
Indep. variables	(1)	(2)	(3)	(4)	(5)	(6)
	−8.26	−2.42	−0.63	1.57	0.76	−1.80
$\beta_{Quant \times SMB}$	−0.1	0	0.06	0.06	−0.19	0.01
	−3.98	−0.04	1.69	1.29	−1.51	0.24
$\beta_{Quant \times HML}$	0.11	−0.02	−0.03	−0.13	0.16	−0.01
	3.36	−0.83	−0.75	−2.04	0.97	−0.11
$\beta_{Quant \times MOM}$	0.06	0	0	−0.02	0.07	−0.02
	5.14	−0.09	0.18	−1.06	1.08	−0.84
$\beta_{Quant \times 10yr}$	−0.12	−0.21	−0.13	−0.31	0.18	−0.09
	−2.69	−5.32	−2.44	−3.77	0.72	−0.87
$\beta_{Quant \times CS}$	−0.19	−0.28	−0.2	−0.34	0.16	−0.12
	−3.35	−5.35	−3.01	−3.17	0.51	−0.85
$\beta_{Quant \times BdOpt}$	0.03	0.01	0	0.02	0.05	−0.00
	6.54	2.85	−0.52	1.91	2.52	−0.39
$\beta_{Quant \times FXOpt}$	−0.01	−0.01	0	−0.02	0	−0.00
	−2.44	−2.92	−0.19	−2.91	−0.14	−0.61
$\beta_{Quant \times ComOpt}$	0.03	0.02	0.01	0.02	0	0.00
	6.8	4.73	1.42	2.03	−0.18	0.44
$\beta_{Quant \times EE}$	−0.1	−0.05	−0.09	−0.07	−0.01	0.01
	−8.86	−5.3	−6.82	−2.88	−0.12	0.59
N	62163	100199	53019	16794	10494	17798
$\overline{R}^2$	0.19	0.15	0.23	0.06	0.22	0.15
Newey w/ 3 Lags	Yes	Yes	Yes	Yes	Yes	Yes
Strategy Control?	No	No	No	No	No	No
Year Controls?	No	No	No	No	No	No
Main HF			EH	M	ED	RV
F-stats and p-values testing exclusion of groups of variables						
Time Effects = 0	109.22	23.99	15.89	4.37	1.03	1.47
	0	0	0	0	0.41	0.13
Fixed Effects = 0	120.08	26.14	17.27	3.91	1.14	1.32
	0	0	0	0	0.33	0.21

5.2. *The composition of deciles*

As another robustness test, we examined the performance of quantitative and qualitative hedge funds by their decile rankings using classification method 1. We looked at their relative performance in two ways. First, we examined the raw returns of both quantitative and qualitative hedge funds. Second, we used the risk-adjusted returns using the 10-factor α. For various time periods, we sorted the performance of these hedge funds from highest to lowest and then computed the percentage of quantitative hedge funds in each decile for the period. Only hedge funds that existed at the beginning and ending of any period were used in the analysis.

More specifically, for each period, hedge fund returns were ranked from highest to lowest by raw return or alpha. They were divided into deciles, where n_1 was the number of quantitative funds used in the analysis for the particular period and n_2 was the number of qualitative funds used in the analysis for the particular period. Decile 1 contained the funds with the lowest returns or $\hat{\alpha}$, while Decile 10 contained the funds with the highest returns or $\hat{\alpha}$. For each performance period, the percentage of quantitative funds in each decile as a percentage of the total number of quantitative funds was computed. Similarly, the percentage of qualitative funds in each decile as a percentage of total qualitative funds was computed. Table 12 reports the difference between the quantitative and qualitative percentage in each decile. The sum of this over all deciles should equal 0. The table also contains the sum of the values of deciles 9 and 10 minus the value of deciles 1 and 2. A positive value of this metric indicates that on average more quantitative funds are in the higher performance deciles relative to qualitative funds.

The raw returns contain mixed evidence. For example, from 1994 to 2000, this value is 17.63, while from 2000 to 2009 it is -19.09. On the other hand, the $\hat{\alpha}$s from the 10-factor model are entirely consistent with quantitative funds outperforming qualitative funds.

6. Conclusion

The growth of hedge fund assets over the last 20 years has been enormous. Thus, an ever important question is whether they can provide better returns than other investment alternatives. Much of the literature finds that hedge funds can perform well on a risk-adjusted basis, since they tend to attract talented people, have less investing restrictions, and have higher incentives. Within the hedge fund world, two camps of management have also grown; the traditional qualitative or fundamental camp and the quantitative camp. The literature has attempted to understand what characteristics of hedge funds might predict superior hedge fund performance. This paper expands that literature by taking a first look at these different types of hedge fund managing styles.

Quantitative and qualitative hedge funds are examined in a variety of ways, including their management differences and their performance differences. The paper finds that management differences among quantitative and qualitative hedge funds are few. First, there are many more qualitative funds with less average assets under management. Second, the average quantitative hedge fund has a larger firm size. Third, the average quantitative hedge fund has more liquidity for investors. Fourth, the average percent of quantitative hedge funds registered with the SEC is less than the average number of qualitative funds.

More importantly for investors, performance differences seem to exist between quantitative and qualitative (or less quantitative) hedge funds over the period from 1994 to 2009. These performance differences might be as high as 72 bps per year on a risk-adjusted basis, which is economically significant. We use two classification methods to separate quantitative and qualitative hedge funds and find the results are similar using both methods. Generally, quantitative funds perform better than qualitative funds using a variety of risk-adjusted performance metrics. For the first classification separation done by hedge fund strategy, these results are consistent with the results of Bali *et al*. (2013) who show that similar hedge fund strategies outperform stock and bond markets, especially during down markets and financial crises.

Although this paper did not directly investigate what specific attributes of quantitative funds might lead to their outperformance, the existing literature points to some potential reasons. Quantitative funds require more mathematics and programming ability and the managers of these funds tend to be highly educated. It may be that the average education of quantitative hedge fund managers is higher leading to higher returns. Li *et al*. (2011)

Table 12

Performance decile composition of quantitative and qualitative hedge funds

This table reports the net percentage of quantitative hedge funds in each performance decile over the respective time period. Only hedge funds that exist at the beginning and ending of the any period are used in the analysis. For this analysis, classification 1 for separating quantitative and qualitative hedge fund was used. For each period, hedge fund returns are ranked from highest to lowest. They are divided into deciles. n_1 is the number of quantitative funds used in the analysis for the particular period, n_2 is the number of qualitative funds used in the analysis for the particular period. Decile 1 contain the funds with the lowest returns or α, while Decile 10 contain the funds with the highest returns or α. For each performance period, the percentage of quantitative funds in each decile as a percentage of the total number of quantitative funds are computed. Similarly, the percentage of qualitative funds in each decile as a percentage of total qualitative funds are computed. The table reports the difference between the quantitative and qualitative percentage in each decile. The sum of this over all deciles should equal 0. Raw returns refers to a simple ranking of actual hedge fund returns net of fees. The Fung-Hsieh 10-Factor α refers to ranking of hedge fund returns by the α generated from the 10-factor model. Factor models are estimated for the period listed. For example, 94-00 estimates the α from the period January 1994 through December 1999.

Decile	94-09	00-09	94-00	00-05	05-09	07-09
			Raw returns			
1	−0.26	0.93	−7.83	−4.41	−6.97	−8.44
2	2.69	5.06	−4.68	3.56	−6.29	−8.14
3	5.64	4.02	1.63	3.09	−3.70	−7.02
4	−6.15	9.18	0.05	1.39	−1.11	−3.23
5	1.03	6.09	0.05	0.28	2.05	−0.10
6	−0.26	−4.75	−3.10	9.18	1.48	0.27
7	−0.26	−6.29	5.57	−0.02	2.63	2.43
8	−3.21	−1.13	3.20	−0.66	−1.40	3.24
9	−3.21	−5.26	0.05	−5.82	5.80	5.70
10	3.97	−7.85	5.07	−6.58	7.52	15.29
$(9+10)-(1+2)$	−1.67	−19.09	17.63	−11.54	26.58	37.57
n1	60	190	199	343	529	685
n2	78	198	350	564	1012	1296
			Fung-Hsieh 10-factor α			
1	2.69	−8.35	−3.10	−0.22	−5.82	−6.88
2	−0.26	−2.16	1.63	−1.63	−4.85	−1.00
3	−3.21	4.02	3.99	3.52	0.61	0.34
4	−0.26	0.93	3.20	−0.22	1.77	1.90
5	6.92	4.53	2.41	1.83	−3.42	0.79
6	−12.05	−1.13	−3.10	0.25	−1.98	−3.00
7	−3.21	−0.10	−3.89	0.71	−1.11	−2.78
8	−3.21	−3.20	−0.74	2.12	0.90	2.80
9	7.31	2.99	1.63	−1.63	2.05	1.68
10	5.26	2.47	−2.03	−4.73	11.84	6.14
$(9+10)-(1+2)$	10.13	15.98	1.07	−4.50	24.57	15.70
n1	60	190	199	344	529	685
n2	78	198	350	564	1012	1296

show that more highly educated hedge fund managers take less risk and produce higher raw and risk-adjusted returns.

It may also be that quantitative managers focus in on anomalies more systematically and make less behavioral errors than less quantitative managers. For example, Frazzini and Pedersen (2013) have shown that buying low beta stocks and selling high beta stocks leads to risk-adjusted outperformance and Eisele (2012) has shown that hedge fund managers that load on this factor have much higher returns than hedge funds that load less on this factor. Quantitative hedge funds have more breadth (i.e. they can find more investment opportunities with their computer programs than a qualitative manager) and thus can find more stocks that are loaded on this and other factors. Recent research has shown that hedge funds that load on certain factors outperform their hedge fund peers. For example, Bali *et al.* (2011) have shown that hedge funds with higher exposure to the default risk premium and lower exposure to the inflation factor have higher subsequent returns. These factors were examined for quantitative and qualitative hedge funds, but there was not a clear enough distinction to explain the outperformance of quantitative funds.

Our paper has shown that quantitative funds also seem to be better market timers than qualitative funds. In fact, it may be precisely the market timing that allows them to outperform the qualitative funds. Although not specifically tested in this paper, it may be that the quantitative hedge funds are timing liquidity and other factors (Cao *et al.*, 2013). To the extent that quantitative hedge funds more precisely load on factors such as this, they might be expected to outperform.

During the quant crisis of 2007, quantitative hedge funds had 10 days of unprecedented return movement, but despite the huge drops in prices, everything returned to normal at the end of the 10 days. Hedge funds that were able to maintain their positions and not liquidate due to margin calls were unharmed from a return perspective. This might explain the overall better performance of quantitative hedge funds. It could be that quantitative funds, being less prone to human behavioral error, do not ‘panic sell’ positions during severe market downturns and thus are able to do particularly well during periods of crisis. Another explanation is that since many of the quantitative hedge funds are constructed to be market neutral, their risks are especially low during crises. In fact, from the data presented in this paper, although qualitative hedge funds performed better during up markets, they performed much worse than quantitative funds during down markets. The annualised risk-adjusted outperformance of quantitative hedge funds over the entire sample period was 72 bps per annum, but during the financial crisis from 2007 to 2009, it was between 264 and 336 bps depending on which classification definition was used. Thus, most of the outperformance came from down markets.

Incentives as expressed through hedge fund incentive fees have been shown to produce higher returns (Agarwal *et al.*, 2009; Edwards and Caglayan, 2001). In our sample data, the evidence was mixed. Using the first classification of quantitative hedge funds, the average incentive fee was lower than qualitative funds by 43 bps, however using the second classification, the average incentive fee was higher than qualitative funds by 78 bps. Thus, the ability of managerial incentives to explain the results is weak. It is left for future research to determine to what extent these differing characteristics may have played a role in the performance differences.

Hedge funds use quantitative techniques to varying degrees. Our separation of hedge funds into quantitative and qualitative is an initial attempt to capture any differences in performance due to quantitative investment techniques. Future research should investigate the sensitivity of these results to other definitions. For example, it might be illuminating to separate quantitative and qualitative hedge funds by their statistical exposures to certain well known quantitative factors, like the momentum factor, the value factor, and others. This would also allow for a larger sample of different types of funds. Future research might also smooth the returns of the hedge fund groups to investigate whether differential smoothing between quantitative and qualitative hedge funds might explain the results (Getmansky *et al*., 2004). Khadani and Lo (2011) document the behaviour of quantitative funds during the financial crisis of 2008 and it might be of interest for future research to understand the risk differences and liquidity exposure differences of quantitative and qualitative funds.

Appendix A: Risk-Adjusted Performance Ratios

Due to the fact that the asset returns of hedge fund strategies are typically not normally distributed, the standard measures of risk-adjusted returns, like the Sharpe ratio, may not be as adequate at describing risk-adjusted performance. For this paper, we look at the Sharpe ratio, as well as several other risk-adjusted measures that better account for non-normality.

The Sharpe Ratio

Our measure of the Sharpe ratio is given by:

$$\text{Sharpe}_i = \frac{\overline{r}_{it} - \overline{r}_{ft}}{\sigma_i} \tag{A.1}$$

where $\overline{r}_{it}$ is the average monthly return of hedge fund i, r_{ft} is the monthly average return of the Fama-French risk-free rate (i.e. one-month Treasury bill rate), and σ_i is the standard deviation of the hedge fund's monthly returns.

The Sortino Ratio

The Sortino ratio is very similar to the Sharpe ratio, except that the denominator of the ratio measures semi-standard deviation, rather than standard deviation. This measures the sample risk more accurately for investors when returns are non-normally distributed and skewed. Our measure is given by:

$$\text{Sortino}_i = \frac{\overline{r}_{it} - \overline{r}_{ft}}{\sqrt{LPM_{2i}(\overline{r}_{it})}} \tag{A.2}$$

where $LPM_{2i}(\tau) = \frac{1}{T}\sum_{i=1}^{T} [\max(\tau - r_{it}, 0)]^2$.

The Omega Ratio

The Omega ratio is very similar to the Sharpe ratio, except that the denominator of the ratio measures only the deviations of returns below zero, without squaring them as is done with a variance calculation. This measures the sample risk more accurately for investors when returns are non-normally distributed and skewed. It is a common reference measure for practitioners. Our measure is given by:

$$\text{Omega}_i = \frac{\overline{r}_{it} - \overline{r}_{ft}}{LPM_{1i}(\overline{r}_{it})} + 1 \tag{A.3}$$

where $LPM_{1i}(\tau) = \frac{1}{T}\sum_{i=1}^{T} [\max(\tau - r_{it}, 0)]^1$.

The Calmar Ratio

The Calmar ratio is a measure who's numerator is similar to the Sharpe ratio. The risk or denominator is measured by the maximum drawdown of the fund over the measurement period. The maximum drawdown is measured as the difference of the fund's NAV from it's peak during the investment period to it's lowest point. One way to think about this measure of risk is that it measures the worst sustainable loss for an investor that bought the fund at its peak and sold the fund at its lowest point. It is a common reference measure for practitioners. Our measure is given by:

$$\text{Calmar}_i = \frac{\overline{r}_{it} - \overline{r}_{ft}}{-MD_{1i}} \tag{A.4}$$

where MD_{1i} is the maximum drawdown of the fund from peak to trough during the existence of the fund in percentage terms.

The Sterling Ratio

The Sterling ratio is a measure who's numerator is similar to the Sharpe ratio. The risk or denominator is measured by the largest drawdowns of the fund over the measurement period. It is similar to the Calmar ratio, however, it does not only consider the largest drawdown, it considers the next largest drawdown, and so on. The maximum drawdown is measured as the difference of the fund's NAV from it's peak during the investment period to it's lowest point. The next drawdown is the next highest NAV to the next to last lowest point, and so on. Our measure is given by:

$$\text{Sterling}_i = \frac{\overline{r}_{it} - \overline{r}_{ft}}{\sum_{j=1}^{N} -MD_{ji}} \tag{A.5}$$

where MD_{1i} is the maximum drawdown of the fund from peak to trough during the existence of the fund in percentage terms, MD_{2i} is the next largest drawdown of the fund in percentage terms, and so on. In the case of the Sterling measure, we take $N = 4$ to represent the four largest drawdowns for the fund during the period of concern. All of the drawdowns are computed by creating an index series of the fund based upon net returns.

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