Hedge Fund Flows and Name Gravitas*

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Abstract

We document that investors allocate more flows to hedge funds whose names exhibit *gravitas* —defined as a combination of words from geopolitics and economics, or suggesting power. The economic effects are relatively large: averaging across our models, adding one more word with gravitas to the name of the average fund brings more than a quarter million dollars more in annual flows. We also document that having a name with gravitas is associated with abnormal negative performance: high name gravitas funds have lower returns, alphas, Sharpe ratios and manipulation-proof performance measures, higher volatilities and maximum drawdowns as well as higher probabilities of extinction than the funds with lower name gravitas. Although we find evidence that investors learn about the true investment abilities of their funds and respond less to gravitas as they do so, the chasing gravitas behavior survives all these controls. From the point of view of hedge fund managers, we document that funds with more name gravitas report to fewer databases, suggesting that giving the fund a "good" name serves as an alternative form of marketing. Finally, we show that our results are robust to a generous battery of additional tests, including corrections for potential endogeneity issues or for whether the fund only accepts qualified investors.

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Hedge Fund Flows and Names Gravitas

John Fortune: In the view of the fact that in these packages there are a lot of dodgy debts, what is it about it that attracts the financial risk takers?

John Bird: Well, it's all because these hedge funds, that specialize in these debts, they all have very good names.

John Fortune: You mean ... they're responsible companies? ...

John Bird: No, no ... this has nothing to do with their reputation, they actually have very good names [...] names like "high," "enhanced" ...

Excerpt from a comedy sketch in which British actor John Bird (playing an investment banker) together with the late actor John Fortune (pretending to interview him) discuss why investors put money into certain Bear Stearns hedge funds containing securitized subprime mortgages (video available on YouTube at https://www.youtube.com/watch?v=mzJmTCYmo9g. 5'18" is the exact timing of discussion.).

1 Introduction

Hedge funds currently manage around three trillion dollars of relatively unregulated capital from sophisticated investors. These investors are perceived to make informed decisions about the funds they consider for holding in their portfolios. Echoing this presumption, the financial economics literature often considers the flows into hedge funds to be "smart money."[1] This view is further reinforced by the fact that these flows are supplied predominantly by the quintessential sophisticated investors, namely, by institutions.[2]

In contrast to this idea of sophistication, we produce direct evidence that hedge fund investors chase hedge fund names containing a special combination of words related to economics and geopolitics, or that convey power. These words are usually associated with weight, influence, authority, seriousness and good judgement - qualities we shall refer to as gravitas.[3] While

[1]Some very recent examples of studies asserting that flows into hedge funds are "smart" are Jacobs (2016) and Akbas, Armstrong, Sorescu, and Subrahmanyam (2015). The point that flows from the hedge funds themselves are smart are made in the opening paragraph of the American Finance Association Presidential Address of Stein (2009) and, for example, by Ben-David, Franzoni, and Moussawi (2012) or Cao, Chen, Goetzmann, and Liang (2016).

[2]For example, the 2016 Deutsche Bank Alternative Investment Survey only mention institutions (including family offices which owned only 4% of the hedge funds assets) while analyzing the types of investors owning hedge funds.

[3]The notion of gravitas has been used, albeit scarcely, in the leadership literature. For example, Hewlett (2014) cites a survey according to which gravitas is the most sought-after quality of an executive. Su and Wilkins (2013) give advice on how to exude gravitas regardless of age and Corkindale (2007) shows how to train executives to improve their gravitas.

it is conceivable that hedge funds' clients may desire their hedge fund managers to exude personal gravitas, what we document is the relatively puzzling fact that investors chase gravitas in the name of the fund itself even after we control for the fund's manager and for the fund's performance. The size of this effect appears to be not only statistically significant and robust to a multitude of specifications and tests, but also economically significant: taking an average across the various models we explore, we estimate that adding one word with gravitas to the name will increase the flow into the average fund by $227,120 every year. In a less intuitive, but perhaps more standard comparison, a one standard deviation increase in gravitas attracts $759,967 more in flows to the average fund every year.

Our choice to focus on name gravitas is not random, as we document that gravitas - considered as a semantic principal component - explains most of the variance in the content of hedge funds' names. Having established the importance of gravitas as a principal component, individual funds' name gravitas is then simply defined as the correlation between the fund's name's content and this principal component. Contrary to the belief that hedge funds names are random, we further document that gravitas is also the principal component with the largest average hedge fund exposure - that is, hedge fund managers tend to prefer gravitas names over the categories suggested by the rest of the principal components.

Investigating the relationship between fund characteristics and name gravitas appears to invalidate the idea that gravitas in name is positively associated with sophistication of the investment approach of the fund. For example, funds with more name gravitas tend to charge higher management fees and lower inventive fees, are less likely to use leverage and have fewer withdrawal restrictions. This suggests that these high gravitas funds employ less sophisticated, more liquid strategies. The propensity of a fund manager to choose a name with gravitas does not seem, therefore, to be a signal of the fund's sophistication. A fact we document that may shed light on the managers' motive is a negative association between name gravitas and the number of databases the hedge fund reports to. As reporting to databases is a form of marketing, this result suggests that naming the fund in a way that appeals to investors is a (less labor-intensive) alternative to traditional indirect ways of marketing the fund.

The lack of sophistication of the investment process is not, however, a necessarily negative attribute of the fund, as simple strategies may in fact exhibit good performance. We therefore investigate whether funds exbiting more name gravitas outperform. The evidence we uncover suggests strongly that just the opposite is true. More precisely, funds with more name gravitas consistently underperform those with the lowest exposure to gravitas. For example, the funds whose names are positively associated with gravitas have annualized alphas that are 0.97% (or 0.73%, when an alternative factor model is used) lower than those of the funds with negative gravitas exposures. Similarly, the annual Sharpe ratios of the high name gravitas funds are 0.18 lower, their average annualized returns are 0.82% lower, their manipulation-proof performance measures[4] are 1.03 lower, the maximum drawdowns are 5.06% higher, and their volatilities are 0.57% higher than those of the funds whose names are negatively associated with gravitas. These differences are also statistically significant for alphas, Sharpe ratios and manipulation-proof performance measures. Although these differences are not statistically significant in the case of returns, for example, their sign is consistent with the assertion that high name gravitas funds underperform. Finally, despite the fact that funds with gravitas receive more flows, we document that these funds have a higher propensity to fail than those with less name gravitas. For example, probit estimations suggest that the probability of attrition of the funds with the highest gravitas measure in our sample is 5.38% higher than that of the funds whose name has no gravitas.

Even though these results are puzzling, they stop short of suggesting that investors allocate flows to funds solely based on their names gravitas and without learning about the manager's true abilities. Indeed, we find support that investors reduce, although not completely eliminate - their name gravitas sensitivity as they learn about the funds. More specifically, we show that flows' response to name gravitas declines with the fund's size as well as with the age of the fund. We also find evidence that as the minimum investment requirements are higher - consistent with the clientèle of that fund being wealthier and potentially more sophisticated - flows respond to gravitas in a less sensitive manner. Furthermore, we show that flows' sensitivity to gravitas is lower for funds whose investors are qualified purchasers.[5] Finally, we additionally find evidence that flows' sensitivity to gravitas declined in the later half of our sample - consistent with the hypothesis that investors became more familiar with hedge funds as an investment vehicle, and also with the idea that the means to perform due diligence and to estimate the quality of hedge funds have recently improved. However, even after controlling for these effects, we document that flows continue to respond statistically significantly to name gravitas.

[4]These measures are defined in Goetzmann, Ingersoll, Spiegel, and Welch (2007).

[5]Funds that are registered under the Section 3(c)(7) of the Investment Company Act cater to "qualified purchasers," defined as investors with at least \$5 million in investments. This is a higher category of sophistication than "accredited investors" who must satisfy a income threshold of at least \$200,000 for the last two years (\$300,000 together with a spouse), expect at least that income in the current year, and have net worth excluding primary residence in excess of \$1 million.

Our paper contributes to the literature in several ways. First, our study adds to the literature addressing the type of managers investors seek (or do not), represented by the recent finance papers directed at firm or manager names such as those of Kumar, Niessen-Ruenzi, and Spalt (2015), Kashmiri and Mahajan (2015), Itzkowitz, Itzkowitz, and Rothbort (2016) or Wu (2010), or by human resources studies such that of Huang and Murnighan (2010). Our paper is close in spirit to that of Cooper, Gulen, and Rau (2005), who, similarly to our study, suggest that "investors are irrationally affected by cosmetic effects." While their paper addresses names of mutual funds, ours is about hedge funds, whose investors are sophisticated and vastly institutional, and thus less prone to behave irrationally.

Second, our paper contributes to the literature addressing determinants of hedge funds flows. The papers belonging to this literature document how investors respond to hedge funds performance (Agarwal and Naik (2004), Fung, Hsieh, Naik, and Ramadorai (2008), Jorion and Schwarz (2015) or Lim, Sensoy, and Weisbach (2015)) or how investors respond to certain fund characteristics (such as, for example, R-squareds as in Titman and Tiu (2011), operational risk measures such as in Brown, Goetzmann, Liang, and Schwarz (2008); Brown, Goetzmann, Liang, and Schwarz (2009); Bollen and Pool (2012); or changes in fees as documented by Agarwal and Ray (2012)). From this literature, our paper is close in spirit to that of Agarwal, Daniel, and Naik (2011), who suggest that hedge funds manage their reported returns to attract more flows. While these authors document that funds with more positive months attract more flows (which gives the managers an incentive to report more positive month-end returns) the study does not analyze whether the practice of managing returns by itself ends up attracting more flows. In contrast, we document that name gravitas, a fund characteristic that remains unchanged during the life of the fund, attracts inflows despite being negatively associated with the fund's performance.

Finally, our paper adds to the growing number of finance papers that are exploiting automation in deciphering semantic content, employing methods proposed by Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008) or Jegadeesh and Wu (2013) and further refined by authors such as Loughran and McDonald (2014) or Hoberg and Maksimovic (2015). Recently, such methods have been extended from the analysis of text to that of speech (Mayew and Venkatachalam (2012)) or images (as in Graham, Harvey, and Puri (2016)). While, similar to these authors, we use automatic semantic interpretation, our task is vastly simplified because we only need to assign meaning to the name of a fund, which is a simple combination of words rather than a complex document.

The rest of the paper is organized as follows. Section 2 describes the data and explains the notion of name gravitas and its construction. Section 3 documents that funds with name gravitas receive more flows. Section 4 presents evidence that funds with name gravitas underperform. Section 5 presents a battery of robustness tests, while Section 6 concludes.

2 Data

In this section we present the main data sources, consisting of hedge funds databases as well as dictionaries assigning meaning to the words in the names of hedge funds.

2.1 Hedge Funds

We form our consolidated hedge fund database by merging records obtained from the BarclayHedge, EurekaHedge, Hedge Fund Research, Lipper TASS, and Morningstar databases. To eliminate duplicates and maintain consistency we use the matching procedure proposed by Joenväärä, Kosowski, and Tolonen (2015). While the hedge funds literature used merged multiple data sets since Fung and Hsieh (2006), our motivation to follow these authors and use multiple data sets stems from the need to measure the propensity of a fund to indirectly market itself by reporting to a number of commercial databases. The sample period is from January 1994 through September 2013 and the sample contains only hedge funds that report their returns on a monthly basis and net of fees. We convert non-USD returns and asset under management values into U.S. dollars using the spot rates obtained from Bloomberg. In order to retain a fund in our sample, we require that the respective fund reveals information on both its compensation structure (incentive fee and high-water mark); on share restrictions (lockup, notice, and redemption periods); and we also require the fund to have at least 24 monthly return observations. Applying these filters yields a sample that contains 17,766 distinct hedge funds, of which 5,898 are active and 11,868 are defunct.

Table I presents the time-series averages of the cross-sectional summary statistics for both time-varying (Panel A) and time-invariant (Panel B) fund characteristics. From the Panel A, we observe that the average fund has a flow of 6.5% per year (although the distribution of flows is skewed, with a median of 0.1% per year), manages $169.1 million (the distribution of size is also skewed, with a median of $36.4 million) and it is 5.32 years old. This average fund charges 1.5% in management fees and 18.1% in incentive fees and it requires a minimum investment of $3 million dollars. 10.3% of these funds have names starting with the letter ”a” while 0.4%

have names starting with a digit. Furthermore, the average fund reported to 1.48 databases at inception and has a name that belongs to 4.21 semantic categories, a notion we will detail in the next subsection.

[Insert Table I]

2.2 Dictionaries and semantic content

In order to assess meaning to the name of a hedge fund we use word categories borrowed from the Harvard IV Psychological dictionary. While using the entire set of 182 categories of words in the dictionary, we first exclude any word that has professional meaning in the hedge fund industry and whose use by finance professionals became commoditized. These words include terms such as "hedge" or "fund," any strategy name or names of standard financial securities.[6] For example, while the word "hedge" may have a negative connotation associated with setting boundaries and limitations to the person unfamiliar with financial vocabulary, it may mean sophistication and unexplained risk taking to the a person moderately versed in financial concepts and it may further mean relatively low volatility associated with illiquidity and relatively few investment constraints to the financial expert. The Harvard dictionary, however, addresses the content of the word from the perspective of the person less familiar with financial concepts and we note that the meaning of a word from finance may be very different to the layman than what it means to the hedge fund expert. This elimination procedure is inspired by Loughran and McDonald (2014), who were the first to make the point that the Harvard IV dictionary categories may not be as useful at explaining finance terms as these categories are in explaining habitual, day-to-day words. While overall the dictionary assigns meaning to 8,661 different words of the English language (some of which having multiple meanings), our exclusion procedure leaves 101 words out, thereby reducing the dictionary used in understanding the content in hedge fund names to 8,560 distinct words.

2.3 What do hedge fund names mean?

In order to interpret the semantic content of hedge funds names, we rely on the technique proposed by Tetlock (2007). To begin with, for every hedge fund we create a vector whose elements correspond to the categories contained in the augmented version of the Harvard IV Psychological dictionary. If one of these semantic categories is present in the name of the fund,

[6] This list is available upon request.

we produce a vector entry counting the instances the category appears in the name. As one word may belong to more than one of the 182 categories in the dictionary, we count the instances in which each category is represented. We then normalize this vector by dividing each element by the sum of all the elements. We do so in order to place the name of one fund into a precise semantic category and to treat funds whose name are simple repetitions of the same categories equally.[7] Panel A of Table II describes the main word categories recorded in the names of hedge funds. From the panel, we observe that terms from economics, politics, verbs descriptive of actions, positive words and words indicating strength are the top five category choices.

[Insert Table II]

Once every hedge fund is assigned a 182-long vector of semantic category weights, we proceed to extract principal components from all these vectors. The first five principal components (sorted by their contribution to variance) explain 43.87% of the total variance in category weights. Panel B of Table II presents the categories aggregating into these top principal components. From the panel we observe that the first component loads up to the POLIT category (words from politics), to ECON (which contains terms from economics), to NATION (a set of words containing country names), to NAME (a geographic extension of NATION which includes in addition continents and geographic regions) and POWTOT (consisting of words which suggest power and influence). We appreciate that this principal component exhibits a mixture of terms suggesting *gravitas*, that is, a combination of seriousness, respect, know-how in politics, exercise of power as well as globalism. The concept of gravitas was highlighted and promoted by the leadership literature in studies such as Hewlett (2014), whose survey data makes gravitas the most desirable characteristic for an executive. In contrast to that literature, our analysis focuses exclusively on the names of the funds rather than on their managers' personalities.

We then measure the exposure of each fund to the principal components (simply as the covariance between the principal component and the semantic weights vector for a fund). Summary statistics related to funds' exposures to the top principal components are reported in Panel C of Table II. From the panel, we observe that in addition to explaining the most amount of variance of the semantic weights vectors, the first principal components also has (from far) the largest average hedge fund exposure (at 0.103, while the next average exposure to a principal

[7]For example, normalizing ensures that two funds hypothetically named "The Awesome Investment Fund" and "The Awesome Awesome Investment Fund" are identically categorized. This is because "investment" and "fund" are professional terms, and hence they are first eliminated. Assuming that "awesome" belongs to out first dictionary category, counted categories produce the vectors $v_1 = [1, 0, ...]$ and $v_2 = [2, 0, ...]$ for the names of the first and respectively the second fund. Normalizing v_1 and v_2 assigns both hedge funds the same name category vector equal to $[1, 0, ...]$.

component is 0.007). It thus appears that the first principal component describes the most popular concepts present in the names of funds. Of course, one concern with principal component analysis is that the definition of the principal components (i.e. the weights defining them) can vastly change depending for example of the sample. However, in unreported tests, we build the first principal component using only data from half of our hedge funds sample (the earliest in terms of inception dates), as well as from the latter half. In both cases, the first principal component has a semantic composition that is very close to that of the gravitas component we constructed using the entire sample of hedge funds.

The variable *Gravitas*, defined as the fund's semantic weights' exposure to the first principal component, will be the focus of our study. Naturally, since the founders decide the names of their funds as well as other fund characteristics (such as, for example, compensation schemes or share restrictions), we expect that name gravitas is related to other fund characteristics considered in the hedge funds literature, and the next subsection explores those relationships.

2.4 Gravitas and fund characteristics

In order to study the relationship between *Gravitas* and different fund characteristics, we regress *Gravitas* on a variety of fund characteristics and report the results of these regressions in Table III. To begin with, a potential concern with investigating whether investors respond to hedge funds name gravitas is that the variable *Gravitas* is fully explained by other fund characteristics. The results in Table III show that this is not the case: the R-squareds of the models we investigate are all under 10%.

[Insert Table III]

The results are useful to paint the picture of the fund whose name has gravitas. To begin with, higher management fees are consistently positively associated with name gravitas in all models explored. More precisely, on average, one standard deviation increase in *Gravitas* is associated with 0.20% more in management fees. Although in two of the eight models considered in Table III the relationship is not statistically significant, incentive fees and *Gravitas* are negatively related, with one standard deviation increase in *Gravitas* corresponding to a 1.69% decrease in incentive fees. If we accept that funds with higher management fees and lower incentive fees are less sophisticated and more likely to underperform[8] then our results are consistent with the less sophisticated, more likely to underperform funds choosing names with more gravitas.

The assertion that less sophisticated funds choose names with more gravitas is further supported by the negative relationship between Lockups/Redemption terms and $Gravitas$,[9] as well as by the negative relationship between $Gravitas$ and the use of leverage by a fund.

In order to elucidate why funds elect to have gravitas-bearing names it is useful to consider the relationship between $Gravitas$ and two particular variables. The first variable is intended to measure a way by which hedge funds market themselves (although indirectly, by getting exposure to potential investors) by reporting to commercially available databases (as argued in Agarwal, Fos, and Jiang (2013)). Since our dataset contains five such databases which do not overlap (Joenväärä, Kosowski, and Tolonen (2015)), we can measure the degree to which hedge funds attempt to capture investor attention by reporting to more than one database. This information is captured by the variable $Number\ of\ DBs$ which represents the number of different databases (from one to five) that a hedge fund reports to.

We document that the relationship between name gravitas and the number of databases to which a fund reports is negative (and statistically significant). This suggests that hedge funds which prefer to report to fewer databases (either because they are resources-constrained or because they prefer to avoid scrutiny on the numbers they report) will elect to name themselves in a way that conveys gravitas. In other words, name gravitas and database reporting appear to be indirect marketing strategy substitutes.

To further strengthen the argument that funds may use their names as a marketing tool, we document a positive relationship between name gravitas and an indicator variable equal to 1 if the name of the fund starts with the letter "a." Having the name listed higher up alphabetically may ensure that the fund gets more investor attention (just as Itzkowitz, Itzkowitz, and Rothbort (2016) document for the names of stocks). We document that funds which attempt to get investors' attention by selecting a name that sits atop of alphabetical lists also prefer giving their name more gravitas. This relationship is statistically significant at higher than 1% significance levels. This result lends consistency to the idea of marketing funds through giving them a "good" name.

[8]See for example Ackermann, McEnally, and Ravenscraft (1999) who document that funds with lower incentive fees or higher management fees underperform, or Agarwal, Daniel, and Naik (2009) who document that funds with greater managerial incentives outperform.

[9]Aragon (2007) document that owing to illiquidity in their investments, funds with higher lockup periods outperform.

Finally, among the possible variables to explain name gravitas we have included some whose relationship with name gravitas is unsurprising. Most notably, higher *Gravitas* is mechanically associated with the presence of a geographical region in the fund's name. From this perspective, it is therefore unsurprising that the indicators $Offshore$ and $UCITS$ are positively correlated with name gravitas.

We continue with the main object of our study, namely, with investigating whether more name gravitas is associated with higher flows.

3 Gravitas and flows

The objective of this section is to investigate whether flows into hedge funds respond to name gravitas. We begin by considering various models of flows into hedge funds in which we add a new variable, namely, *Gravitas*.

3.1 Baseline model

We start our analysis in the most basic fashion by calculating quarterly flows into hedge funds and then running panel and Fama and MacBeth (1973) regressions of flows on *Gravitas*. Specifically, we consider the following model:

$$
\begin{aligned}
Flow_{i,t} = {} & \gamma_0 + \gamma_1 Gravitas_i \\
& + \gamma_2 Alphabet_i + \gamma_3 Digit_i + \gamma_4 \log(Number\ of\ DBs_{i,t-1}) \\
& + \gamma_5 Offshore_i + \gamma_6 UCITS_i \\
& + \gamma_7 Gravitas_i \times LowRank_{i,t-1} + \gamma_8 Gravitas_i \times MidRank_{i,t-1} + \gamma_9 Gravitas \times HighRank_{i,t-1} \\
& + \gamma_{10} LowRank_{i,t-1} + \gamma_{11} MidRank_{i,t-1} + \gamma_{12} HighRank_{i,t-1} \\
& + \gamma_{13} TimeVaryingControls_{i,t-1} + \gamma_{14} TimeInvariantControls_i + \varepsilon_{i,t}.
\end{aligned}
\tag{1}
$$

Section 2.4 argues that funds may attempt to market themselves using names not only by giving their names gravitas but also by ensuring that the funds are listed higher up in the alphabetical order. For this reason we include controls for whether the fund has a name that begins with the letter "a" (the indicator variable *Alphabet*) or with a digit (the indicator *Digit*).

In Section 2.4 we also argued that an alternative to use the name of the fund as a marketing tool, hedge funds may elect to report to commercially available databases. Since flows may respond to this tactic we control for the number of databases a hedge fund reports to. Moreover, Aragon, Liang, and Park (2013) argue that flows into onshore funds and their offshore "twins" are different. In addition, gravitas in name tends to be correlated with the fund having a more global approach in its investment process and perhaps its investors. For these reasons it is important that we control for these effects, and we do so by adding the indicator variables $Offshore$ as well as $UCITS$.

Although we include name gravitas in our analysis, this model builds on the large literature addressing determinants of flows. As in this literature Sirri and Tufano (1998) document that flows into mutual funds are a convex function of past performance and in order to accommodate for that functional relationship we include past performance separately for low, medium and high-performance rank funds. More precisely, as standard in the literature we include the variables $LowRank_{i,t-1}$, $MidRank_{i,t-1}$ and $HighRank_{i,t-1}$ as controls.[10] Just as they treat performance differently depending on whether the fund is a low, medium or high performer, investors may also respond to gravitas in name differently depending on past performance rank. For this reason, in addition to including the $LowRank$, $MedRank$ and $HighRank$ variables in our model we also include interactions between $Gravitas$ and these performance indicators.

The convex shape of the flow-performance relationship for mutual funds exists partly because investors are free to move in and out from their investments. This is not the case for hedge funds, whose share restrictions may prevent investors from pulling out of their hedge funds. As argued by Getmansky, Liang, Schwarz, and Wermers (2015) the presence of share restrictions modifies the flow-performance relationship and for this reason we include controls for lockups and redemption periods.

Furthermore, we control for funds' age and assets under management, as well as past flows. In addition, Agarwal, Daniel, and Naik (2004) argued that incentives given to hedge fund managers affect flows, and we consequently control for management and incentive fees. We also control for heterogeneity in hedge funds investment styles by including strategy fixed effects. Finally, our analysis is cross-sectional in nature, and thus we include time fixed effects, and cluster our panel standard errors by fund. These control variable are summarized by the two (multidimensional) variables $TimeVaryingControls$ and $TimeInvariantControls$.

[Insert Table IV]

[10] These variable are defined using a fractional rank ($FRANK$) representing a fund's percentile performance relative to other funds. The lowest performance tercile ($LowRank_{i,t-1}$) is defined as $Min(1/3, FRANK_{i,t-1})$; the middle performance tercile ($Mid_{i,t-1}$) is defined as $Min(1/3, FRANK_{i,t-1} - Low_{i,t-1})$; and the highest performance tercile ($High_{i,t-1}$) is defined as $Min(1/3, FRANK_{i,t-1} - Low_{i,t-1} - Mid_{i,t-1})$.

The results of our analysis are presented in Table IV. From the table, we readily observe that in all models considered we reject the null hypothesis of no relationship between flows and name gravitas at significance levels higher than 1% in favor of the alternative that flows respond positively to gravitas. Not only is this relationship statistically significant but it is economically significant as well. For example, averaging the response of flows to gravitas across all models considered, one standard deviation increase in gravitas attracts 0.455% more flows every year (annual average flow is 6.5%). In dollar terms, for the average fund (which manages \$167 million) this amounts to \$759,967 more per year in flows. A less standard (but perhaps more intuitive) way to convey the magnitude of the economic effect is to see the increased flow response to the addition of one more word with gravitas to the name of the fund. First, we may calculate the average number of different categories present in the name of a hedge fund, which is 6.095. This does not mean that the average hedge fund has around 6 words in the name because certain words belong to more than one semantic category. In addition, from Table II the average exposure to gravitas is 0.103, and thus adding one more term to the name amounts to $0.103/6.095 = 0.017$ more gravitas exposure. The average coefficient on gravitas in the models considered in Table IV (which is built using quarterly flows) is 0.020, and therefore adding one more term to the name of the average fund attracts $0.020 \times 0.017 \times 4$ more in annual flows. Multiplying further by average fund size, this amounts to \$227,120 more in annual flows to the average fund.

As appealing as being listed high up alphabetically can be as a marketing technique, Table IV documents no particular relationship between flows and the *Alphabet* or *Digit* indicators. However, consistent with the idea that getting the fund on investors lists is useful, being listed in several databases does appear to attract more flows.

Examining the interaction terms $Gravitas \times Rank$ reveals some interesting results. First, we note that the positive relationship between flow and gravitas is weaker for those funds that are the lowest performers, as the coefficient on $Gravitas \times Low\ rank$ is negative and statistically significant at 1% confidence level. This is indicative that investors responding positively to name gravitas are doing it less enthusiastically for those funds that are low performers. For funds with intermediate past performance, however, the flow response to gravitas is stronger as performance increases. More precisely, absent powerful indicators that the fund is either clearly outperforming (such as having a high performance rank) or clearly underperforming, investors respond to gravitas stronger as the past performance of the fund was better while the fund remained in the mid performance rank category. This result hints that investors rely on name gravitas to infer potential information about the fund and when other available sources offer information that is equivocal or imprecise (as indicated by the fund being a mid-performer) investors put more reliance on name gravitas. Finally, for high performers, the interaction between rank and gravitas is statistically insignificant.

The coefficients on the control variables are not unexpected given the findings in the literature. For example, consistent with emerging managers outperforming (and thus attracting flows), such as documented by Aggarwal and Jorion (2010), size and fund age both have negative and significant coefficients in the flow regressions.

While these results are presented for quarterly flows, they hold at annual levels as well. Furthermore, the coefficients of *Gravitas* remain positive and significant when different models (in addition to those presented in Table IV) are considered. We can then conclude that hedge fund with more name gravitas attract more flows.

3.2 Name gravitas or manager gravitas?

The results of the previous section associate positive name gravitas with more flows. However, one possibility is that investors do not react to the name of the fund per se, but to qualities of the fund manager that are likely to be reflected in the name of the fund. For example, it is conceivable that funds with gravitas in their name also have charismatic managers, with a magnetic personality that compels investors to trust these mangers with their money. This possibility is realistic considering the survey results of Hewlett (2014), who claims that gravitas is the most desirable trait of an executive, and hedge funds executives should be no different. In this case, the effect documented in the previous section would be an investtors' reaction to people, rather than to names.

In order to control for this possibility, we reduce our data to a matched sample, where the matching is done either by manager, or by firm. More precisely, for example, when we match by manager we only include pairs of fund-dates where the funds are managed by the same manager while the names are such that one is positively correlated with gravitas while the other has a negative correlation. If our result is caused by the magnetic personality of the managers rather than by the gravitas in the name of the fund itself, we should see no relationship between name gravitas and flows when we perform our analysis on the matched sample.

[Insert Table V]

The results from this test are presented in Table V. Although our matching procedure reduces the size of the dataset by more than seven times when we match by firm, and by more than 20 times when we match by manager, the results presented in Table V are very strongly supportive of the assertion that investors' flows respond not to the manager of the fund or to the firm but to the name of the fund itself.

One other possibility, however, is that the same manager gives the funds she manages different names, with the gravitas names being reserved for the flagship of the family. For this reason, it is very important to control for past performance in the matched sample regressions, and we certainly include those controls in out tests.

Taken at face value, the results of this section allude to investors behaving irrationally, in a way similar to responses to fund name changes in Cooper, Gulen, and Rau (2005) or to foreign-sounding manager names as in Kumar, Niessen-Ruenzi, and Spalt (2015). However, in contrast to mutual fund investors, hedge fund investors are sophisticated, and consist of mostly institutions.

Although it appears irrational to chase fund names, this behavior may in fact be optimal if name gravitas positively predicts performance. In this case, their gravitas chasing behavior means that hedge fund investors are smart and allocate assets to future outperforming funds, whose good performance is predicted by their high name gravitas. This is a real possibility given the existence of hot hands among hedge fund managers (such as documented by Jagannathan, Malakhov, and Novikov (2010)). It is however questionable behavior, as Baquero and Verbeek (2009) document that investors are unable to systematically exploit the hot hands phenomenon persistently. In the next section, we investigate whether high name gravitas funds outperform.

4 Name gravitas and performance

The objective of this section is to analyze the relationship between name gravitas and subsequent hedge funds performance and risk. We will do so by regressing widely used measures of performance, such as excess returns or alphas, on name gravitas, by constructing portfolios of high and low gravitas funds and exploiting their performance differences, as well as by analyzing the survival probabilities of high and low gravitas funds.

4.1 Regression analysis: name gravitas, returns, and alphas

In order to start our investigation of the relationship between name gravitas and fund performance, we regress excess quarterly returns on name gravitas, along with a variety of fund characteristics. Since our data is obtained by merging several datasets, we do not have information regarding the time a fund started to report and we are unable to solve the problem of backfilling bias completely. In addition to presenting results using the entire time series of available returns for each fund, therefore, we also follow Kosowski, Naik, and Teo (2007) and present results after we eliminate the first 12 months from each fund's history.[11] These tests are presented in Table VI. The main takeaway from the table is that there appears to be no positive or significant relationship between name gravitas and excess returns. In fact, in all the models considered this relationship is negative — and in one model statistically significant at 5% confidence level. It appears therefore that high name gravitas does not predict subsequent higher excess returns.

[Insert Table VI]

However, subtracting the riskfree rata from the returns of the hedge funds may not constitute a risk adjustment that is appropriate for every investor. We therefore consider hedge funds alphas as measured first by the classical model of Fung and Hsieh (2004) as well as its version augmented with an Emerging Markets index from Fung and Hsieh (2001).[12] We follow Agarwal, Daniel, and Naik (2009) to calculate quarterly alphas, by assuming that factor loadings are constant so that residuals and factor returns vary every month. The quarterly alpha is calculated as the sum of the alphas and the residuals of all the months of that quarter. Once we calculate the alphas, we regress them on the same variables as we did excess returns. The results, presented in Table VII, fail to find any positive correlation between name gravitas and hedge fund alphas. In fact, just as in our tests for excess returns, all the models exhibit negative correlations between gravitas and alphas. Furthermore, in one case (that when no return observations are dropped and when we calculate Fung and Hsieh (2004) 7-factors alphas) the correlation is also statistically significant at a 5% level.

[Insert Table VII]

[11] However, in results available upon request, we replicate our results after eliminating 24 months and also for a subsample of funds for which the date at which they joined the databases is available. In these additional tests there are no qualitative changes of the results reported in this study.

[12] We thank David Hsieh for making the relevant data available at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

In summary, in our regression analysis we find a negative –albeit nearly always insignificant– relationship between gravitas and performance.

4.2 Portfolio of funds with positive and negative name gravitas

While the results presented do not to find that name gravitas predicts fund outperformance, they are falling short of supporting the thesis that investors in funds with high name gravitas are behaving irrationally. This is due to two reasons. First, our tests fail to provide support for the thesis that high name gravitas predicts in fact underperformance because the coefficients on *Gravitas* are not statistically significant (with one exception in the case of excess returns and another for the alphas). Second, although excess returns and alphas are widely used in practice and in academic studies, there is in addition a plethora of measures of performance and risk measures that are relevant to hedge funds investors.[13] In order to address these problems, we sort funds based on their name gravitas and form three portfolios: that of the funds with positive name gravitas, that of the funds whose name gravitas is equal to zero and the portfolio of the funds whose name gravitas is negative. For these portfolios, we estimate excess returns, Fung and Hsieh 7 or 8-factor alphas as well as exposure to the specific Fung and Hsieh factors, volatilites, Sharpe ratios, the manipulation-proof performance measures of Goetzmann, Ingersoll, Spiegel, and Welch (2007) as well as maximum drawdowns from peak. We then calculate differences between each of these measures when applied to the positive name gravitas and, respectively, to the negative name gravitas portfolios. The tests statistics of the differences are then calculated using Newey and West (1987) for all the performance and risk measures except for R-squareds and maximum drawdowns, in which case we use bootstrapped statistics as in Politis and Romano (1994). These latter statistics are viewed in the literature as conservative. We present the results of this analysis in Table VIII.

[Insert Table VIII]

From Panel A, we first observe that portfolio differences are consistent with the results of the regressions from Table VI. As seen in Panel A of Table VIII, the portfolio of funds with positive gravitas has 0.82% less average annual returns than then funds with negative gravitas. Just like in our previous test, this difference is not statistically significant. The rest of Panel A conveys that positive gravitas funds are riskier and underperform negative gravitas funds. For example, the portfolio of positive gravitas funds has an annual volatility that is 0.57% higher than that

[13] For example, Eling and Schuhmacher (2007) use no less than 13 such measures.

of the portfolio of negative gravitas funds (and the difference is statistically significant, with a t-statistic of 3.30). Moreover, the Sharpe ratio of the positive gravitas portfolio is 0.18 lower (on annual terms) than that of the negative gravitas portfolio and this difference is also statistically significant. Finally, the maximum drawdown of the positive gravitas portfolio is 5.05% higher. All these results indicate that from the point of view of performance (either risk adjusted or not), and risk, funds with high name gravitas are inferior to those with low gravitas.

Panels B1 and B2 extend this conclusion to the Fung and Hsieh alphas. In contrast to Table VII, however, the alpha differences between the portfolio of positive gravitas funds and the portfolio of negative gravitas funds are now statistically significant. They are also economically significant at -0.97% per year and -0.78% per year, respectively, depending on whether we use a 7 or an 8-factor Fung and Hsieh model. The appraisal ratio differences are statistically significant as well, with the positive gravitas funds having lower appraisal ratios than the negative gravitas funds. These results are further consistent with the hypothesis that name gravitas predicts underperformance.

4.3 Gravitas and survival

In this subsection we analyze the relationship between name gravitas and a fund's propensity to survive and continue to report to databases. In order to do so, we consider probit as well as Cox hazard models where the dependent variable is either an attrition indicator (equal to 1 if the fund reports to databases currently but stops reporting next month; this is presented in Table IX, Panel A) or an indicator of fund failure (equal to 1 if the fund failed according to the classification proposed by Liang and Park (2010); these results are presented in Panel B of Table IX).

[Insert Table IX]

The leftmost columns of both Panels A and B convey support to the hypothesis that high name gravitas funds are more likely to suffer both attrition and failure, regardless of whether the test ran is a probit regression or a Cox proportional hazards model. The statistical significance is much higher when the probit model approach is employed. Also, we observe that the relative effect of gravitas is nearly twice as important to predict failure of a fund (marginal effect equal to 9.0%) than it is to predict attrition (where the marginal effect is equal to 5.6%).

The result that funds with more name gravitas go under more frequently may seem at odds with our earlier finding that these funds raise more capital. In order to understand why name gravitas affects the probability of failure and attrition positively (despite at the same time positively affecting inflows), it is useful to add interaction terms between *Gravitas* and past performance to our analysis. This amounts to changing the functional form of the coefficient on *Gravitas* from a constant γ_0^{const} to a conditional random variable equal to $(\gamma_0 + \gamma_1 Low\ Rank + \gamma_2 Mid\ Rank + \gamma_3$ For example, in the case of estimating failure rates using the Cox proportional hazard model, the coefficient estimations are (as seen in the first and respectively third columns of Panel B) $\widehat{\gamma_0^{const}} = 0.179, \widehat{\gamma_0} = -0.565,\ \widehat{\gamma_1} = 5.833,\ \widehat{\gamma_2} = -0.167$ and $\widehat{\gamma_3} = -5.840$. Of the last four estimations, only those for γ_0 and γ_1 are statistically significant. From here, we deduce that the overall positive effect of gravitas on failure rates (as implied by $\widehat{\gamma_0^{const}} > 0$) comes solely from the funds in the worst performance quartile (as implied by $\widehat{\gamma_1} > 0$). In other words, the low performing, high gravitas funds tend to fail with such a high propensity that it appears that *overall*, funds with high name gravitas are more prone to fail. The same type of argument applies to both probit and Cox estimations for both attrition as well as failure rates.

We can therefore conclude, given that high name gravitas funds underperform and in addition are more prone to fail, that investors appear to behave irrationally by allocating capital to these funds.

5 Investors' learning and robustness of results

Having justified that investors behave irrationally by selecting funds based on their high name gravitas, we turn to investigating whether our results are robust to hegde funds investors learning about the true investment abilities of these funds. After all, because the name rarely changes for hedge funds,[14] name gravitas remains the same throughout the fund's life — and the question is then whether investors' response to gravitas is mitigated, or completely subsumed by learning.

Furthermore, in addition to studying whether the effect we document disappears as investors learn, it is also instructive to address potential endogenous issues faced by our tests. This section addresses both robustness issues, those related to learning by investors as well as those pertaining to endogenenity.

[14] While the hedge funds literature has documented returns restatements (Patton, Ramadorai, and Streatfield (2015)) or fee changes (Agarwal and Ray (2012)), anecdotal evidence suggests that name changes are rare. However, when such name changes happen, what we learned from private conversations is that the changes are made to attract more flows. For example, if a strategy is "hot," funds may add a reference of that strategy to their name if such a reference was missing. We control for such possibilities by including strategy controls in our analysis.

5.1 Learning by investors

In order to analyze the impact of learning on flow response to name gravitas, we start with the baseline model (1) and add interaction terms between gravitas and fund characteristic that indicate either that investors know more about a fund as these characteristics improve (such as the fund's age, or size); fund characteristics that suggest a more sophisticated clientèle (such as minimum investment); or indicators for periods when investors are less (or more) prone to learn about the true investment abilities of the funds in which they invest (e.g., a bull market indicator). The results of these tests are presented in Table X.

[Insert Table X]

To start with, it goes without saying that investors will know more about funds that are older. Consistent with this assertion, we observe that the coefficient on $Gravitas \times Lagged\ age$ in Table X is negative and statistically significant at 1% level. That is, the flows' response to name gravitas declines with the fund's age. It is interesting to investigate how old should the fund be, on average, for the flow response to name gravitas to be flat. In order to calculate that threshold age, we can make the conditional estimator of coefficient on gravitas equal to zero, that is, $0.018 - 0.002 \times age = 0$. This produces a threshold age of $age = 9$ years, twice the median age of a fund in our data and quite a long time until learning completely nullifies the propensity to allocate capital because the name of the fund has gravitas.

Next, funds that are larger have more sophisticated clientèles and arrived at their current size during some time period during which investors learn more about the fund. Examining Table X, the interaction term is negative and significant at 1% level suggesting that the irrational response of flow to name gravitas declines as funds are larger. As with age, we can identify the size threshold that makes the flows response to name gravitas equal to zero by solving the equation $0.039 - 0.008 \log(AUM) = 0$. Since AUM is expressed in \$ million, the solution to that equation produces a threshold size larger than that of any existing fund. We conclude that although the flow's response to name gravitas is smaller as funds become larger, it does not disappear completely.

We then examine whether funds with more investment restrictions (such as lockups or longer redemption notice periods) experience a reduced flow response to their name gravitas. The corresponding estimation of the interaction term between *Gravitas* and *Restriction* is negative but it is however insignificant. While funds with more severe restrictions arguably have more sophisticated investors (because their investment strategies are also more sophisticated, requiring more liquidity management), studying the flows into and out of these funds is complicated by the very existence of the liquidity constraints themselves. This in turns makes the estimation of the model with interaction terms more difficult.

Minimum investment requirements are another signal that the fund has a more sophisticated clientèle. Therefore, we expect that funds with higher minimum investment requirements experience a more subdued flow response to name gravitas. Indeed, examination of the coefficient on the interaction term $Gravitas \times Minimum\ investment$ in Table X reveals that the estimation is negative and statistically significant at 10% confidence level. The minimum investment threshold past which flows will not positively respond to gravitas is estimated, based on the results reported in the table, to be over \$50 million - a possible, but unusually high level.

In the previous tests we analyzed separately the funds that are larger, have more restrictions or have higher minimum investment requirements. Our rationale for separately considering these funds was to test if these funds' clients - presumably sophisticated investors - still chase name gravitas, and we found support for this assertion. We will next focus on a direct control for sophisticated investors. More precisely, we consider running our tests controlling for, as well as interacting *Graviats* with whether the fund is registered under the Section 3(c)(7) of the Investment Company Act ("the Act"). The section stipulates that a fund may have up to 2,000 investors if they are "qualified purchasers" - that is, individuals or companies closely held having no less than \$5 million in investments (a good discussion of the legal status of hedge funds can be found in Flood and Monin (2016)). Being registered under Section 3(c)(7) of the Act therefore serves as a proxy for having more sophisticated clients, at least more sophisticated than the accredited investor normally allowed to invest in a hedge fund. We therefore correct for the fund being a 3(c)(7) entity by adding an indicator variable equal to 1 if the fund is registered as such, as well for the interaction between this indicator variable and *Gravitas*. Since not all of the databases report the legal status of the fund, the indicator variable for 3(c)(7) essentially reduces our panel in nearly half the number of observations, from 17,766 funds to 7,054 funds. Of the funds for which the data is available, 24.1% are registered using the Section 3(c)(7) of the Act. To the best of our knowledge, this is the first study using the 3(c)(7) variable.

From the analysis, we observe that even after controlling directly for the presence of sophisticated investors, the coefficient of *Gravitas* is positive and statistically significant at 1% confidence level. We also observe that the coefficient on the interacting term between the 3(c)(7) indicator and *Gravitas* is negative - consistent with the fact that the presence of sophisticated investors reduces the positive response of flows to name gravitas. However, we conclude that even the presence of very sophisticated investors does not eradicate the irrational chasing of gravitas in funds' names.

We now turn our attention to variables indicative of time periods in which learning about funds' investment abilities weakens or intensifies. One example is periods of bull markets. In bull markets, both funds with high market exposures and funds with lower market exposures but higher alphas experience overall positive performance, making it more difficult to distinguish the funds with ability to generate positive alphas from the rest. Bull markets, therefore, are periods when it is more difficult to learn a fund's true investment abilities and consequently we expect flows to respond even stronger to name gravitas during bull markets. As seen in the table, however, although the coefficient on the $Gravitas \times Bull$ is positive (that is, consistent with the idea that in bull markets the flow response to gravitas is more pronounced), it is statistically insignificant.

To continue with the discussion of periods in which investors learn about funds' abilities differently we turn our attention to the second half of the sample. In the recent half of our sample, investors' ability to learn about hedge funds increased considerably as hedge funds, consistent with the prediction of Stulz (2007), became more institutionalized and studied, as well as better understood. We therefore include in our analysis an indicator variable *Late* that is equal to 1 for the period post December 2005. The coefficient on the the interaction term between *Gravitas* and *Late* is negative and significant at 1% level, consistent with the assertion that in the latest period investors learned about funds and responded in a more muted way to name gravitas.

Finally, in the way of robustness checks for our main result that funds with more name gravitas attract more flows, we observe that after the inclusion of all the variables mentioned in this section as well as interaction terms between them and *Gravitas*, the coefficient of *Gravitas* remains positive and significant at 1% level. In addition to these robustness tests that were motivated by investors learning about funds, we also run a large battery of additional tests that are standard relative to what the literature suggests.[15] In particular, we consider removing 24 months of returns when correcting for the backfilling bias, or running our analysis on smaller subsamples where we correct for backfilling using the precise dates at which funds join the databases. We also add or remove variables in a variety of ways, or we consider annual variables (such as flows) rather than their quarterly counterparts. In all these specifications, flows

[15]The results of these tests are available upon request.

appeared to chase name gravitas. We can conclude the subsection affirming strong support in favor of our main result.

5.2 Endogeneity problems

In this subsection we investigate a potential endogeneity problem, which occurs as follows. While flows always arrive after the name of the fund is set, it is possible that a fund investigates the possibility to raise capital before it incorporates, and when this investigation is successful, opens under a name that reflects the founders' early success. Assuming the manager is talented, flows will follow, but in this case the gravitas in the name followed the success of the early founding capital rather than the other way around.

In order to control for this potential problem we employ an instrumental variable approach. As an instrument for name gravitas, we propose the number of words in the name of the fund (more precisely, $\log(1 + Number\ of\ words)$). The exclusion criterion is satisfied because the number of words is influencing the flows only through its influence on gravitas. If the number of words affects flows through another mechanism, most likely this mechanism is that of inattention, that is, an investor will allocate less flows to a fund with more words in the name because it will require too much effort to read that name. We however found very little support for inattention as Table IV documents that funds starting with the letter "a" do not attract more flows. The choice of the instrument, therefore, seems validated and we run a 2-stage regression to control for potential endogeneity issues with our main result.

In the first state we regress *Gravitas* on our instrumental variable, namely, the number of words in the fund's name. The coefficient of the number of words in this estimation is positive and highly significant, again providing support for our choice of the instrumental variable. We then retrieve the estimation of *Gravitas* from the first stage regression and use it as an independent variable in the second stage of the procedure. The results of this 2SLS procedure are presented in Table XI.

[Insert Table XI]

From Panel A of Table XI we observe that the instrumental variable approach confirms our main results presented in Table IV, that funds with high name gravitas attract more flows. In Panel B of Table XI we then replicate the more general models meant to verify the robustness of our tests that we presented in Table X. The results of all the tests are very strong - in both Panels A and B, the coefficients on the estimation of *Gravitas* are positive and significant at

1% level. We thus provided support that our result is not caused by funds starting to invest and selecting a name with gravitas because of a promise of early flows made before the fund is started. This concludes our battery of robustness verifications.

6 Conclusions

As The Economist put it in Schumpeter (2015), companies in general are continuously looking up for good names, as the name is the first impression they make upon a potential client. While this may be understandable for a company attempting to attract an individual who is inexperienced and perhaps susceptible to be tricked by the cleverness of a name, it is, to say the least, a puzzling effect to be found with hedge funds investors.

The hedge funds industry's clients are supposed to be, by contrast to individuals, sophisticated, and are mostly institutions, in theory more immune to behavioral decision making biases. Yet we document that behavioral sensitivities still exist. This is in sharp contrast with the null hypothesis that virtually no variables derived from names alone should be in any way predictive of hedge funds flows.

Although our results are disconcerting, on a note of optimism we documented that investors also learn about the funds' abilities, and that hedge funds with low performance and gravitas in names are eventually punished, oftentimes severely enough that they exit the sample altogether.

While some authors document that hedge fund managers themselves may be influenced by behavioral factors,[16] a fact that is perhaps unsurprising given that the hedge funds industry has lower barriers of entry, our paper is the first to document the presence of a bias in the decision making process of (sophisticated) hedge fund investors. We hope it to open the door to a more careful examination of the actions of sophisticated investors in general.

[16]For example, Lu, Ray, and Teo (2016) document that managers with marital problems suffer from inattention that results in lower performance. Brown, Lu, Ray, and Teo (2016) document that managers who buy sport cars take more risk and have lower Sharpe ratios.

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Table I: Summary Statistics

This table presents summary statistics of fund characteristic. Panel A (and respectively, Panel B) presents time-varying (time-invariant) fund characteristics. “N” is number of monthly observations (that are time-varying) or number of funds (that are time-invariant). “Mean” (Std) is the cross-sectional average (standard deviation) of a particular fund characteristic. “Median” is the 50th percentile of that characteristic. “Return” is the monthly average of a hedge fund’s excess return. “Flow” is the fund's quarterly flow measured in percentage of total assets. “Size” is the fund’s assets under management, measured in millions U.S. dollars. “Age” is the fund’s age, measured in years from inception date. “Number of DBs (dynamic)” is the number of databases a fund reports at a given month. “Alive” refers to the portion of funds that are still reporting at the period’s end. “High-water mark” indicates the percentage of funds imposing a high-water mark provision. “Management fee” gives the management fee charged by the funds, while “Incentive fee” is the performance-based fee charged by the funds. “Lockup dummy” is an indicator variable that takes on a value of 1 if the fund has a lockup period and 0 otherwise. “Restriction” is defined as the sum of redemption period and notice period. “Minimum investment” is the minimum amount of money in U.S. dollars that has to be invested in the fund. “Qualified Purchasers” is an indicator variable that takes value of 1 when the fund is registered under the Section 3(c)(7) of the Investment Company Act (“the Act”) and otherwise 0. “Alphabet” is an indicator variable that is 1 if the fund name starts with the letter ‘a’ and 0 otherwise. “Digit” is an indicator variable that is 1 if the fund name starts with a digit and 0 otherwise. “UCITS” is an indicator variable that is 1 if the fund is UCITS-compliant, and 0 otherwise. “Offshore” is an indicator variable that is 1 if the fund is domiciled in offshore location and 0 otherwise. “Number of DBs (at inception)” is the number of databases a fund reports at the fund inception. “Number of words” refers to the number of words a fund name contains.

Panel A: Time-varying Fund Characteristics

	N	Mean	Median	Std
Return	303,331	0.024	0.020	0.111
AUM	303,331	169.139	36.400	673.131
Flow	303,331	0.065	0.001	0.341
Age	303,331	5.232	3.917	4.528
Number of DBs (dynamic)	303,331	1.753	1.000	1.141

Panel B: Time-invariant Fund Characteristics

	N	Mean	Median	Std
Alive	17,766	0.332		
High-water mark	17,766	0.800		
Management fee	17,766	0.015	0.015	0.006
Incentive fee	17,766	0.181	0.200	0.060
Lockup dummy	17,766	0.287		
Restriction	17,766	0.282	0.179	0.267
Leverage dummy	17,766	0.577		
Minimum investment	16,554	2.985	0.250	55.136
Qualified Purchasers	7,054	0.241	0.000	0.428
Alphabet	17,766	0.103		
Digit	17,766	0.004		
UCITS	15,000	0.043		
Offshore	17,766	0.434		
Number of DBs (at inception)	17,766	1.481	1.000	0.914
Number of words	17,766	4.213	4.000	1.469

Table II: Summary Statistics of Fund Name Principal Components

This table presents the information on hedge funds names content. Panel A presents the top word categories. Panel B presents the category weights of principal components. Panel C presents the summary statistics for hedge fund names exposures to principal components.

Panel A: Top Word Categories

Rank	Category	# of instances	What is it
1	ECON	6 617	510 words of an economic, commercial, industrial, or business orientation, including roles, collectivities, acts, abstract ideas, and symbols, including references to money. Includes names of common commodities in business.
2	POLIT	5 298	507 words having a political character, including political roles, collectivities, acts, ideas, ideologies, and symbols.
3	IAV	4 665	1,947 verbs giving an interpretative explanation of an action, such as “encourage, mislead, flatter”.
4	POSITIV	4 358	1,915 words of positive outlook. (It does not contain words for yes, which has been made a separate category of 20 entries.)
	PSTV	3 269	(A more restricted category for positive)
5	STRONG	4 335	1902words implying strength.
6	POWTOT	4 112	1226 words of a valuing of having the influence to affect the policies of others.
7	ACTIVE	4 096	2045 words implying an active orientation.
8	VIRTUE	3 525	719 words indicating an assessment of moral approval or good fortune, especially from the perspective of middle-class society.
9	ENDSLW	3 140	270 words of desired or undesired ends or goals.
10	WLTTOT	2 822	378 words related to wealth.

Panel B: Category Weights of Top Principal Components (PC)

PC1		PC2		PC3		PC4		PC5	
POLIT	0.54	POSITIV	0.46	NATION	0.80	QUAN	0.75	PLACE	0.66
ECON	0.47	ENDSLW	0.40	POSITIV	0.13	OVRST	0.31	QUAN	0.39
NATION	0.45	VIRTUE	0.39	VIRTUE	0.12	UNDRST	0.07	AQUATIC	0.28
NAME	0.41	PSTV	0.36	PSTV	0.12	CAUSAL	0.06	POSITIV	0.22
POWTOT	0.21	MEANS	0.25	EVAL	0.06	NUMB	0.05	VIRTUE	0.22

Panel C: Statistics for Name Exposure to Principal Components (PC)

	N	Mean	Median	Std	Min	Max
PC1	17,766	0.103	0.000	0.231	-0.147	0.931
PC2	17,766	0.003	0.000	0.056	-0.149	0.414
PC3	17,766	0.007	0.000	0.037	-0.222	0.418
PC4	17,766	-0.004	0.000	0.047	-0.35	0.428
PC5	17,766	0.003	0.000	0.057	-0.219	0.514

Table III: Determinants of Name Gravitas

This table presents results from cross-sectional regressions in which Gravitas, the fund names' exposure to the first principal component of fund name content, is regressed on time-invariant fund-characteristics. We include strategy fixed effects among the independent variables (we report the coefficients of the strategy dummies with self-explanatory names as well as an Other strategy). The fixed effect coefficients for the short bias style cannot be estimated due to degeneracy, and is not shown. The definitions of the fund characteristics are from Table I. The *t*-statistics (presented in parenthesis) are calculated using White standard errors.

	Gravitas							
High-water mark	0.016	0.006	0.017	0.008	0.018	0.007	0.012	0.004
	(3.60)	(1.52)	(3.89)	(1.77)	(3.81)	(1.54)	(2.70)	(0.96)
Management fee	1.099	0.804	1.115	0.824	1.075	0.672	0.768	0.628
	(4.27)	(3.20)	(4.33)	(3.28)	(3.86)	(2.47)	(2.98)	(2.48)
Incentive fee	-0.112	-0.046	-0.108	-0.043	-0.081	-0.02	-0.121	-0.055
	(-4.00)	(-1.69)	(-3.86)	(-1.58)	(-2.63)	(-0.67)	(-4.32)	(-2.04)
Lockup dummy	-0.043	-0.037	-0.043	-0.037	-0.042	-0.035	-0.035	-0.033
	(-11.49)	(-10.07)	(-11.39)	(-9.99)	(-10.00)	(-8.47)	(-9.47)	(-8.84)
Restriction	-0.051	-0.047	-0.051	-0.047	-0.045	-0.042	-0.049	-0.045
	(-7.87)	(-7.33)	(-7.91)	(-7.36)	(-6.09)	(-5.71)	(-7.72)	(-7.14)
Leverage dummy	-0.007	-0.001	-0.008	-0.001	-0.006	0.001	-0.011	-0.003
	(-2.09)	(-0.25)	(-2.14)	(-0.31)	(-1.46)	(0.18)	(-3.07)	(-0.99)
Log(Number of DBs)	-0.008	-0.007						
	(-2.04)	(-1.90)						
Alphabet			0.025	0.022				
			(4.11)	(3.82)				
Digit			0.009	0.007				
			(0.29)	(0.23)				
UCITS					0.036	0.025		
					(3.32)	(2.42)		
Offshore							0.05	0.033
							(13.73)	(9.16)

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Table III (cont'd)

CTA		-0.044		-0.044		-0.044		-0.041
		(-2.41)		(-2.37)		(-2.16)		(-2.25)
Emerging Markets		0.170		0.170		0.172		0.163
		(8.88)		(8.84)		(8.08)		(8.52)
Event Driven		-0.012		-0.012		-0.013		-0.014
		(-0.65)		(-0.62)		(-0.61)		(-0.73)
Global Macro		-0.036		-0.036		-0.034		-0.038
		(-1.93)		(-1.91)		(-1.63)		(-2.07)
Long Only		0.024		0.025		0.022		0.028
		(1.13)		(1.14)		(0.96)		(1.29)
Long/Short		0.035		0.036		0.038		0.036
		(1.92)		(1.93)		(1.84)		(1.95)
Market Neutral		0.004		0.006		0.004		0.006
		(0.22)		(0.30)		(0.18)		(0.33)
Multi-Strategy		-0.022		-0.022		-0.019		-0.023
		(-1.22)		(-1.20)		(-0.91)		(-1.25)
Others		-0.016		-0.016		-0.017		-0.018
		(-0.84)		(-0.83)		(-0.81)		(-0.94)
Relative Value		-0.023		-0.021		-0.025		-0.022
		(-1.24)		(-1.16)		(-1.20)		(-1.21)
Sector		-0.031		-0.031		-0.036		-0.029
		(-1.68)		(-1.63)		(-1.73)		(-1.57)
Short Bias		0		0		0		0
Intercept	0.122	0.095	0.125	0.097	0.117	0.091	0.112	0.090
	(18.61)	(5.12)	(19.06)	(5.17)	(15.89)	(4.33)	(16.98)	(4.83)
AdjR2	1.7 %	9.3 %	1.7 %	9.2 %	1.6 %	9.5 %	2.7 %	9.7 %
N	17,766	17,766	17,766	17,766	15,000	15,000	17,766	17,766

Table IV: Fund Flows and Name Gravitas

This table presents results from regressions in which quarterly fund flows are regressed on Gravitas and a set of control variables. Past performance controls consists of the variables Low rank, Mid rank and High rank that are defined using a fractional rank (FRANK) representing a fund's percentile performance relative to other funds in the same investment strategy during the quarter. The lowest performance tercile (Low rank) is defined as Min (1/3, FRANK); the middle performance tercile (Mid rank) is defined as Min (1/3, FRANK - Low rank); and the highest performance tercile (High rank) is defined as Min (1/3, FRANK - Low rank - Mid rank). The rest of the variables are defined in Table I. The regressions ran are panel (Panel) with style and time fixed effects and standard errors clustered at the fund level, as well as Fama-MacBeth (FM) with style fixed effects; fixed effects are not shown in the tables. All variables, except Gravitas, are winsorized at 1% and 99% levels. *T*-statistics are shown in parenthesis.

	Quarterly Flow									
	Panel	FM	Panel	FM	Panel	FM	Panel	FM	Panel	FM
Gravitas	0.010	0.016	0.044	0.054	0.010	0.016	0.010	0.016	0.008	0.013
	(3.44)	(2.75)	(4.53)	(3.55)	(3.47)	(2.79)	(3.24)	(2.72)	(2.84)	(2.22)
Alphabet	-0.000	-0.002	-0.000	-0.002	-0.000	-0.002	-0.001	-0.001	-0.000	-0.002
	(-0.09)	(-0.56)	(-0.07)	(-0.47)	(-0.12)	(-0.57)	(-0.36)	(-0.27)	(-0.19)	(-0.51)
Digit	0.020	0.004	0.019	0.002	0.019	0.004	0.028	0.010	0.020	0.004
	(1.53)	(0.27)	(1.45)	(0.16)	(1.49)	(0.27)	(2.31)	(0.63)	(1.59)	(0.26)
Log(Number of DBs)					0.006	0.008				
					(4.95)	(4.41)				
UCITS							0.025	0.015		
							(4.70)	(1.25)		
Offshore									0.010	0.012
									(6.79)	(3.10)
Gravitas x Low rank			-0.294	-0.310						
			(-4.81)	(-4.33)						
Gravitas x Mid rank			0.066	0.064						
			(4.06)	(1.90)						
Gravitas x High rank			-0.048	-0.153						
			(-0.63)	(-1.42)						
Low rank	0.206	0.223	0.237	0.252	0.207	0.224	0.195	0.226	0.205	0.219
	(13.90)	(8.11)	(14.46)	(8.62)	(13.95)	(8.08)	(12.54)	(7.04)	(13.78)	(8.01)
Mid rank	0.152	0.172	0.146	0.166	0.152	0.171	0.149	0.172	0.152	0.172
	(41.66)	(18.14)	(36.72)	(16.68)	(41.61)	(18.13)	(38.54)	(17.60)	(41.72)	(18.07)
High rank	0.053	0.038	0.057	0.046	0.053	0.039	0.065	0.051	0.055	0.042
	(2.80)	(1.09)	(2.75)	(1.37)	(2.78)	(1.11)	(3.21)	(1.32)	(2.87)	(1.21)

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Table IV (cont'd)

Lagged size	-0.019	-0.021	-0.019	-0.021	-0.019	-0.022	-0.019	-0.022	-0.02	-0.022
	(-42.40)	(-17.56)	(-42.39)	(-17.69)	(-42.35)	(-17.51)	(-39.04)	(-15.62)	(-42.33)	(-17.90)
Lagged age	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(-34.85)	(-13.20)	(-34.90)	(-13.18)	(-34.93)	(-13.24)	(-31.80)	(-13.34)	(-33.90)	(-14.06)
Lagged flow	0.176	0.166	0.176	0.166	0.176	0.165	0.179	0.171	0.176	0.165
	(51.75)	(22.46)	(51.74)	(22.53)	(51.72)	(22.47)	(47.85)	(21.52)	(51.80)	(22.31)
High-water mark	0.014	0.012	0.014	0.012	0.013	0.01	0.018	0.017	0.013	0.011
	(6.79)	(4.17)	(6.81)	(4.16)	(6.28)	(3.86)	(8.25)	(4.89)	(6.46)	(4.22)
Management fee	0.466	0.428	0.466	0.435	0.468	0.436	0.421	0.418	0.403	0.369
	(3.25)	(2.04)	(3.26)	(2.08)	(3.27)	(2.08)	(2.75)	(1.99)	(2.80)	(1.83)
Incentive fee	-0.007	-0.002	-0.007	-0.002	-0.011	-0.007	-0.02	-0.013	-0.011	-0.005
	(-0.49)	(-0.13)	(-0.50)	(-0.13)	(-0.77)	(-0.44)	(-1.33)	(-0.79)	(-0.74)	(-0.36)
Lockup dummy	-0.008	-0.007	-0.008	-0.007	-0.008	-0.008	-0.008	-0.009	-0.006	-0.006
	(-5.27)	(-3.39)	(-5.26)	(-3.39)	(-5.46)	(-3.61)	(-5.12)	(-4.11)	(-4.34)	(-2.65)
Restriction	0.008	0.006	0.008	0.006	0.008	0.007	0.01	0.009	0.009	0.01
	(3.11)	(1.32)	(3.11)	(1.35)	(3.18)	(1.38)	(3.57)	(2.14)	(3.70)	(2.02)
Leverage dummy	0.000	0.001	0.000	0.001	0.000	0.001	0.002	0.005	0.000	0.000
	(0.09)	(0.35)	(0.17)	(0.34)	(0.10)	(0.51)	(1.35)	(2.17)	(-0.34)	(0.08)
AdjR2	10.1 %	10.0 %	10.1 %	10.1 %	10.1 %	10.0 %	10.4 %	10.9 %	10.1 %	10.1 %
N	284,975	284,975	284,975	284,975	284,975	284,975	246,003	246,003	284,975	284,975

Table V: Fund Flows and Matched Fund Pairs within Same Company or Same Manager

This table presents quarterly panel regression results for the matched funds within a hedge fund firm (Panel A) or the matched funds that are managed by the same fund manager side-by side (Panel B). Both samples include only the fund-date pairs in which one of the fund-pair names exhibits positive correlation with Gravitas and another of the fund-pair names exhibits negative correlation with Gravitas. Funds whose names have zero correlations with Gravitas are excluded. The dependent variable is the Quarterly flow while the main independent variable is Gravitas. Definitions of control variables can be found in Tables I and IV. The panel regressions include style and time fixed effects (which for brevity are not shown in the table) and standard errors are clustered by firm or manager (*t*-statistics are shown in parenthesis). All variables, except Gravitas, are winsorized at 1% and 99% levels.

	Panel A: Within the Same Firm				Panel B: Within the Same Manager			
	Quarterly flow				Quarterly flow			
Gravitas	0.015	0.015	0.018	0.013	0.024	0.029	0.027	0.022
	(2.47)	(2.43)	(2.93)	(2.17)	(2.59)	(2.32)	(2.80)	(2.25)
Low rank	0.150	0.149	0.178	0.150	0.062	0.060	0.093	0.061
	(3.58)	(3.57)	(4.28)	(3.58)	(0.91)	(0.88)	(1.54)	(0.89)
Mid rank	0.155	0.155	0.153	0.155	0.163	0.163	0.163	0.163
	(16.28)	(16.30)	(15.18)	(16.28)	(10.89)	(10.91)	(10.62)	(10.92)
High rank	0.023	0.023	0.051	0.023	0.063	0.064	0.087	0.063
	(0.43)	(0.42)	(0.91)	(0.43)	(0.76)	(0.77)	(1.07)	(0.76)
Alphabet	-0.005	-0.006	-0.006	-0.005	0.006	0.006	0.010	0.006
	(-0.87)	(-0.89)	(-0.86)	(-0.85)	(0.70)	(0.64)	(1.01)	(0.70)
Digit	0.008	0.007	0.027	0.009	0.058	0.058	0.060	0.057
	(0.29)	(0.26)	(0.98)	(0.31)	(1.13)	(1.11)	(1.16)	(1.11)
Log(Number of DBs)		-0.003				-0.002		
		(-0.95)				(-0.32)		
UCITS			0.028				0.048	
			(3.42)				(2.26)	
Offshore				0.006				0.008
				(1.75)				(1.29)
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AdjR2	10.1 %	10.1 %	10.9 %	10.1 %	10.3 %	10.3 %	10.6 %	10.3 %
N	40,207	40,207	34,739	40,207	14,849	14,849	13,634	14,849

Table VI: Hedge Fund Returns and Name Gravitas

This table presents results from regressions of quarterly fund excess returns on Gravitas as well as a set of control variables that are defined in Table I and also used in Table IV. The regressions are panel (Panel) with style and time fixed effects and with standard errors clustered by fund, as well as Fama-MacBeth (FM) with style fixed effects. Fixed effects are not shown in the tables. All variables, except Gravitas, are winsorized at 1% and 99% levels. *T*-statistics are in parentheses.

	Quarterly excess return All obs.		Quarterly excess return First 12m dropped	
	Panel	FM	Panel	FM
Gravitas	-0.002	-0.004	-0.001	-0.002
	(-2.01)	(-1.54)	(-1.12)	(-1.01)
Low rank	-0.003	-0.006	0.003	-0.002
	(-0.50)	(-0.18)	(0.54)	(-0.05)
Mid rank	0.025	0.023	0.025	0.024
	(27.30)	(4.96)	25.16	(4.70)
High rank	0.131	0.136	0.117	0.119
	(19.18)	(4.78)	(16.40)	(4.07)
Lagged size	-0.001	-0.001	-0.001	-0.001
	(-14.16)	(-4.12)	(-9.78)	(-2.67)
Lagged age	-0.000	-0.000	-0.000	-0.000
	(-3.92)	(-2.47)	(-0.17)	(-1.62)
Lagged flow	0.002	0.002	0.002	0.001
	(4.79)	(1.89)	(3.46)	(1.05)
High-water mark	0.004	0.003	0.004	0.003
	(6.57)	(3.53)	(6.18)	(3.35)
Management fee	0.127	0.13	0.124	0.142
	(3.23)	(1.79)	(3.05)	(1.86)
Incentive fee	0.009	0.018	0.001	0.01
	(2.56)	(2.33)	(0.35)	(1.16)
Lockup dummy	0.002	0.002	0.002	0.003
	(3.96)	(2.74)	(3.69)	(3.40)
Restriction	(0.01)	(0.01)	(0.00)	(0.01)
	(7.66)	(3.10)	(5.59)	(2.21)
Leverage dummy	-0.001	0.000	-0.001	0.000
	(-2.16)	(-0.39)	(-1.44)	(0.20)
Adj. R^2	19.80 %	16.90 %	20.60 %	17.20 %
Obs.	286,951	286,951	244,353	244,353

Table VII: Hedge Fund Alphas and Name Gravitas

This table presents the results of regressions of hedge fund alphas on Gravitas as well as a variety of control variables. Alphas are calculated using either a 7-factor Fung and Hsieh model or an 8-factor model (the eighth factor are the returns of the MSCI Emerging Markets Index). The regressions are panel (Panel) with style and time fixed effects and with standard errors clustered by fund, as well as Fama-MacBeth (FM) with style fixed effects. Fixed effects are not shown in the tables. All variables, except Gravitas, are winsorized at 1% and 99% levels. *T*-statistics are in parentheses.

	Quarterly Fung-Hsieh 7-factor Alpha				Quarterly Fung-Hsieh 8-factor Alpha			
	All obs.		First 12m dropped		All obs.		First 12m dropped	
Variable	Panel	FM	Panel	FM	Panel	FM	Panel	FM
Gravitas	-0.002	-0.003	-0.001	-0.001	-0.001	-0.002	-0.0001	-0.0001
	(-2.01)	(-1.44)	(-1.32)	(-0.69)	(-1.53)	(-1.06)	(-0.62)	(-0.24)
Low rank	-0.000	0.001	0.007	0.009	-0.004	-0.005	0.003	0.002
	(-0.04)	(0.03)	(1.32)	(0.42)	(-0.80)	(-0.27)	(0.55)	(0.12)
Mid rank	0.017	0.019	0.016	0.019	0.017	0.018	0.016	0.019
	(22.21)	(6.69)	(20.12)	(6.59)	(22.14)	(6.81)	(20.46)	(7.24)
High rank	0.069	0.069	0.056	0.064	0.066	0.073	0.053	0.063
	(13.16)	(3.86)	(10.23)	(3.42)	(12.88)	(4.67)	(9.77)	(3.87)
Lagged size	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.000	-0.000
	(-9.02)	(-3.75)	(-4.29)	(-1.96)	(-8.30)	(-3.10)	(-3.72)	(-1.27)
Lagged age	-0.000	-0.001	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000
	(-11.58)	(-4.87)	(-8.11)	(-3.69)	(-11.71)	(-4.72)	(-8.00)	(-3.69)
Lagged flow	0.003	0.002	0.003	0.002	0.002	0.002	0.003	0.001
	(-6.41)	(2.33)	(5.21)	(1.59)	(6.44)	(2.56)	(5.07)	(1.43)
High-water mark	0.004	0.004	0.004	0.003	0.004	0.004	0.004	0.003
	(8.26)	(4.95)	(8.03)	(4.24)	(7.65)	(5.53)	(7.58)	(4.79)
Management fee	0.164	0.166	0.14	0.135	0.124	0.151	0.100	0.12
	(4.12)	(2.98)	(3.48)	(2.19)	(3.19)	(2.97)	(2.55)	(2.16)
Incentive fee	0.022	0.028	0.016	0.022	0.021	0.026	0.016	0.020
	(6.13)	(5.34)	(4.48)	(4.20)	(6.20)	(5.65)	(4.62)	(4.50)
Lockup dummy	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.002
	(1.67)	(2.25)	(1.85)	(2.86)	(2.12)	(2.11)	(2.28)	(2.75)
Restriction	0.004	0.004	0.002	0.003	0.004	0.004	0.003	0.003
	(4.86)	(2.94)	(3.31)	(1.86)	(5.88)	(3.71)	(4.33)	(2.56)
Leverage dummy	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000
	(-1.15)	(-0.74)	(-1.01)	(-0.60)	(-1.04)	(-1.06)	(-0.98)	(-0.91)
AdjR^2	7.00 %	9.80 %	6.90 %	9.50 %	4.80 %	7.30 %	4.50 %	7.20 %
Obs	278,989	278,989	242,479	242,479	278,989	278,989	242,479	242,479

Table VIII: Performance Differentials between Funds with Negative and Positive Name Gravitas

This table presents performance differentials between portfolios of the funds with positive Gravitas exposure ("Pos. Grav."), with zero exposure ("Neu. Grav.") and with negative Gravitas exposure ("Neg. Grav."). Panel A presents differences between absolute performance statistics of the portfolios. "Mean return" is the portfolio's mean return and "Volatility" is its standard deviation, both in annualized percentage; "Sharpe" is the Sharpe ratio, or the mean return divided by its standard deviation (annualized); "MPPM" is the annualized manipulation-proof performance measure of Goetzmann et al. (2007) as estimated using a risk-aversion coefficient of 5; and "MaxDD" is the maximum drawdown. Panels B1 and B2 present differences in alphas and factor exposures relative to the Fung and Hsieh 7- and 8-factor models. "Alpha" is the annualized intercept of the benchmark regression; "IdioVola" is annualized standard deviation of residual term; "Appraisal" is alpha divided by its residual volatility (annualized). The seven benchmark factors are: the S&P 500 return minus the risk-free rate (SP); returns on the Russell 2000 index minus the S&P 500 index return (SIZE); excess return on 10-year US Treasury bonds (CGS10); the yield spread between 10-year T-bonds and Moody's Baa-rated bonds (CREDSPR); and the so-called primitive trend-following strategy for bonds (PTFSBD), currency (PTFSFX), and commodities (PTFSCOM). The eighth factor is the returns of the MSCI Emerging Markets Index (MSEMKF). "R^2" is the adjusted R-square of the benchmark regression. The first 12 months of returns were dropped from each fund's data to correct for backfilling bias.

Panel A: Fund absolute performance statistics

	Mean # of funds	Minimum # of funds	Maximum # of funds	Mean return	Volatility	Sharpe	MPPM	MaxDD
Neg. Grav.	666	82	1,139	6.650	7.133	0.932	5.315	21.657
Neu. Grav.	1,512	250	2,391	6.804	6.928	0.982	5.561	20.241
Pos. Grav.	1,069	144	1,850	5.827	7.705	0.756	4.289	26.719
Difference				-0.823	0.572	-0.176	-1.026	5.061
Test statistic				(-1.59)	(3.30)	(-2.65)	(-2.04)	(1.54)

Panel B1: 7-factor Fung and Hsieh Alphas and Exposures

	Alpha	IdioVola	Appraisal	SP	SCLC	CGS10	CREDSPR	PTFSBD	PTFSFX	PTFSCOM	R^2
Neg. Grav.	3.564	3.857	0.924	0.304	0.187	0.033	0.190	-0.010	0.008	0.007	69.80 %
Neu. Grav.	3.855	3.619	1.065	0.295	0.194	0.023	0.188	-0.007	0.008	0.005	71.82 %
Pos. Grav.	2.596	4.328	0.600	0.301	0.186	0.019	0.279	-0.009	0.011	0.003	67.42 %
Difference	-0.967	0.471	-0.324	-0.003	-0.001	-0.013	0.089	0.001	0.004	-0.005	-2.39 %
Test statistic	(-2.00)	(3.07)	(-2.72)	(-0.18)	(-0.07)	(-0.58)	(3.72)	(0.20)	(1.93)	(-1.98)	(-0.94)

Panel B2: 8-factor Fung and Hsieh Alphas and Exposures

	Alpha	IdioVola	Appraisal	SP	SCLC	CGS10	CREDSPR	PTFSBD	PTFSFX	PTFSCOM	MSEMKF	R^2
Neg. Grav.	3.995	3.275	1.220	0.166	0.134	0.038	0.099	-0.006	0.007	0.006	0.138	78.12 %
Neu. Grav.	4.238	3.134	1.353	0.172	0.147	0.028	0.108	-0.004	0.008	0.004	0.123	78.77 %
Pos. Grav.	3.211	3.206	1.002	0.105	0.110	0.027	0.150	-0.004	0.011	0.001	0.197	82.03 %
Difference	-0.783	-0.069	-0.218	-0.061	-0.024	-0.011	0.050	0.002	0.004	-0.005	0.059	3.91 %
Test statistic	(-1.93)	(-0.42)	(-1.67)	(-3.96)	(-1.88)	(-0.55)	(2.06)	(0.76)	(2.00)	(-2.26)	(6.69)	(1.40)

Table IX: Fund Failure and Name Gravitas

This table presents Cox Semiparametric Hazards Model and Probit Model analyses. In Panel A, the dependent indicator variable taking value of 1 if the fund stops reporting in subsequent period, and otherwise 0. In Panel B, the dependent indicator variable takes value of 1 when the Liang and Park (2010) fund failure conditions are met (i.e., negative six-month average return, plus negative 12-month change in AUM), and otherwise 0. As explanatory variables are used the first principal component of fund name content (Gravitas) and a set of control variables that are defined in Table I and IV. The all models include both style and time fixed effects (not shown), standard errors clustered at the fund levels (*t*-statistics are shown in parenthesis). All explanatory variables, except Gravitas, are winsorized at 1% and 99% levels.

	Panel A: Attrition				Panel B: Failure			
	Cox	Probit	Cox	Probit	Cox	Probit	Cox	Probit
Gravitas	0.113	0.056	-0.311	-0.170	0.179	0.090	-0.565	-0.270
	(1.68)	(2.64)	(-1.89)	(-2.52)	(1.77)	(2.57)	(-2.51)	(-3.12)
Gravitas x Low rank			3.235	1.640			5.833	2.737
			(2.93)	(3.66)			(3.46)	(4.50)
Gravitas x Mid rank			-0.361	-0.160			-0.167	-0.256
			(-1.18)	(-1.24)			(-0.28)	(-1.09)
Gravitas x High rank			-1.568	-0.648			-5.840	-1.626
			(-1.10)	(-1.09)			(-1.17)	(-1.03)
Low rank	-2.755	-1.475	-3.085	-1.645	-4.984	-2.551	-5.641	-2.854
	(-8.80)	(-13.96)	(-9.47)	(-14.34)	(-9.68)	(-17.26)	(-10.20)	(-17.67)
Mid rank	-1.178	-0.529	-1.141	-0.512	-3.440	-1.369	-3.416	-1.34
	(-10.57)	(-17.67)	(-9.52)	(-15.68)	(-11.72)	(-22.99)	(-11.20)	(-20.15)
High rank	-0.197	-0.062	-0.040	0.004	-2.245	-0.820	-1.649	-0.660
	(-0.55)	(-0.43)	(-0.10)	(0.03)	(-1.16)	(-2.24)	(-0.82)	(-1.67)
Lagged size	-0.198	-0.099	-0.198	-0.099	-0.231	-0.112	-0.231	-0.112
	(-26.70)	(-35.93)	(-26.80)	(-35.91)	(-14.93)	(-26.13)	(-14.94)	(-26.11)
Lagged age	0.005	0.003	0.005	0.003	-0.006	-0.002	-0.006	-0.002
	(1.74)	(2.84)	(1.76)	(2.88)	(-1.02)	(-1.23)	(-0.99)	(-1.19)
Lagged flow	-1.278	-0.516	-1.277	-0.515	-2.729	-1.316	-2.729	-1.315
	(-16.81)	(-14.38)	(-16.82)	(-14.36)	(-22.44)	(-31.56)	(-22.55)	(-31.55)
High-water mark	-0.368	-0.183	-0.369	-0.184	-0.273	-0.136	-0.278	-0.137
	(-4.51)	(-12.86)	(-4.53)	(-12.88)	(-3.85)	(-6.05)	(-3.93)	(-6.10)
Management fee	7.648	3.607	7.617	3.595	9.528	4.074	9.349	4.039
	(3.19)	(3.88)	(3.18)	(3.87)	(2.51)	(2.82)	(2.51)	(2.79)
Incentive fee	1.630	0.803	1.627	0.801	1.420	0.681	1.416	0.676
	(4.79)	(8.11)	(4.78)	(8.08)	(2.99)	(4.19)	(2.99)	(4.16)
Lockup dummy	-0.061	-0.031	-0.061	-0.031	-0.104	-0.053	-0.105	-0.054
	(-1.87)	(-2.73)	(-1.88)	(-2.73)	(-1.89)	(-2.84)	(-1.91)	(-2.87)
Restriction	0.288	0.134	0.289	0.134	0.220	0.105	0.223	0.107
	(3.65)	(6.47)	(3.67)	(6.48)	(2.10)	(3.03)	(2.11)	(3.06)
Gen. R-squared		2.2 %		2.3 %		2.5 %		2.5 %
N	312,981	312,981	312,981	312,981	263,915	263,915	263,915	263,915

Table X: Fund Flows and Name Gravitas Interaction Terms

This table presents quarterly regressions of fund flow on Gravitas, on interaction terms between Gravitas and several variables defined below, and a set of control variables. Gravitas is interacted with fund age and size as well as minimum investment, 3(c)7 hedge fund (than only accepts qualified purchasers as fund investors) and restriction period. To test for the flow sensitivity to Gravitas separately in bear and bull markets, Gravitas is interacted with Bull market indicator getting a value of 1 when the returns on SP500 index are above the median of the SP500 index over the full sample, and otherwise 0. To test for the flow sensitivity to Gravitas separately in early and late sample periods, Gravitas is interacted with Late sample indicator getting a value of 0 prior to December 2005, and otherwise 1. Regressions include a set of control variables that are identical to those used in Table IV. Table presents results for panel regression with style and time fixed effects and standard errors clustered by fund (*t*-statistics are shown in parenthesis). All variables, except Gravitas, are winsorized at 1% and 99% levels.

	Quarterly Flow						
Gravitas	0.018	0.039	0.013	0.017	0.015	0.010	0.026
	(3.56)	(4.11)	(2.90)	(4.00)	(3.00)	(2.71)	(4.71)
Gravitas x Lagged age	-0.002						
	(-2.10)						
Gravitas x Lagged size		-0.008					
		(-3.65)					
Gravitas x Restriction			-0.011				
			(-0.91)				
Gravitas x Minimum investment				-0.010			
				(-1.76)			
Minimum investment				0.016			
				(9.61)			
Gravitas x 3(c)7 hedge fund					-0.026		
					(-2.38)		
3(c)7 hedge fund					0.018		
					(7.46)		
Gravitas x Bull						0.000	
						(0.03)	
Bull						-0.011	
						(-1.69)	
Gravitas x Late							-0.027
							(-4.15)
Late							-0.031
							(-4.93)
Lagged size	-0.019	-0.019	-0.019	-0.020	-0.020	-0.019	-0.019
	(-42.39)	(-38.37)	(-42.40)	(-41.28)	(-29.44)	(-42.40)	(-42.42)
Lagged age	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(-32.06)	(-34.98)	(-34.86)	(-32.94)	(-25.39)	(-34.85)	(-34.86)
Restriction	0.008	0.008	0.009	0.003	0.003	0.008	0.008
	(3.04)	(3.08)	(3.18)	(1.24)	(0.85)	(3.11)	(3.17)
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AdjR2	10.1 %	10.1 %	10.1 %	10.0 %	10.6 %	10.1 %	10.1 %
N	284,975	284,975	284,975	259,968	137,188	284,975	284,975

Table XI: Two-stage Regressions: Fund Flows and Name Gravitas

This table present results of 2SLS regressions. At the first stage, Gravitas is instrumented by the Number of words in hedge fund name, fund characteristics and style dummies (as in Table III). In the second stage, quarterly flows are regressed on fitted values of name Gravitas obtained from the first stage OLS. Variable definitions are from Table I to IV. The Panel regression models include style and time fixed effects and standard errors clustered by fund (*t*-statistics are shown in parenthesis). Fixed effects are not shown in the table for brevity. All variables, except fitted values of Gravitas, are winsorized at 1% and 99% levels.

Panel A: Results in Table IV replicated using 2SLS

	Gravitas	Quarterly Flow				
	1. stage	2. stage				
Gravitas		0.130	0.274	0.129	0.136	0.115
		(6.06)	(8.21)	(6.02)	(5.96)	(5.27)
Log(1 + Number of words)	0.117					
	(21.00)					
Alphabet		0.000	0.000	0.000	-0.000	-0.000
		(0.05)	(0.05)	(0.02)	(-0.20)	(-0.06)
Digit		0.022	0.021	0.021	0.030	0.022
		(1.65)	(1.64)	(1.62)	(2.42)	(1.70)
Log(Number of DBs)				0.006		
				(4.88)		
UCITS					0.022	
					(4.14)	
Offshore						0.009
						(6.39)
Gravitas x Low rank			-0.902			
			(-5.45)			
Gravitas x Mid rank			0.078			
			(1.74)			
Gravitas x High rank			-0.209			
			(-0.95)			
Low rank		0.204	0.297	0.204	0.192	0.203
		(13.73)	(12.75)	(13.78)	(12.37)	(13.64)
Mid rank		0.152	0.144	0.152	0.148	0.152
		(41.66)	(24.64)	(41.61)	(38.52)	(41.71)
High rank		0.057	0.080	0.057	0.069	0.058
		(3.01)	(2.56)	(2.99)	(3.44)	(3.05)

(cont'd on the next page)

Table XI (cont'd)

Lagged size		-0.019	-0.019	-0.019	-0.019	-0.02
		(-42.47)	(-42.53)	(-42.41)	(-39.09)	(-42.45)
Lagged age		-0.006	-0.006	-0.006	-0.005	-0.006
		(-33.52)	(-33.55)	(-33.61)	(-30.55)	(-32.75)
Lagged flow		0.176	0.176	0.176	0.179	0.176
		(51.77)	(51.75)	(51.74)	(47.87)	(51.82)
High-water mark	-0.002	0.013	0.013	0.013	0.018	0.013
	(-0.39)	(6.53)	(6.55)	(6.04)	(7.98)	(6.25)
Management fee	0.592	0.381	0.377	0.383	0.324	0.331
	(2.37)	(2.66)	(2.64)	(2.68)	(2.12)	(2.30)
Incentive fee	0.005	-0.003	-0.003	-0.007	-0.016	-0.007
	(0.20)	(-0.21)	(-0.21)	(-0.48)	(-1.07)	(-0.48)
Lockup dummy	-0.032	-0.003	-0.003	-0.004	-0.003	-0.003
	(-8.79)	(-2.06)	(-2.08)	(-2.24)	(-1.93)	(-1.60)
Restriction	-0.033	0.014	0.014	0.014	0.016	0.015
	(-5.45)	(5.05)	(5.04)	(5.10)	(5.43)	(5.34)
Leverage dummy	-0.002	-0.000	0.000	-0.000	0.002	-0.001
	(-0.54)	(-0.02)	(0.06)	(-0.01)	(1.27)	(-0.42)
Adj. R2		10.1 %	10.1 %	10.1 %	10.4 %	10.1 %
N		284,975	284,975	284,975	246,003	284,975

Panel B: Results in Table X replicated using 2SLS

	Quarterly Flow					
	2. stage					
Gravitas	0.166	0.189	0.119	0.170	0.145	0.179
	(6.66)	(5.98)	(5.05)	(6.80)	(6.46)	(7.37)
Gravitas x Lagged age	-0.007					
	(-3.10)					
Gravitas x Lagged size		-0.017				
		(-2.89)				
Gravitas x Restriction			0.040			
			(1.27)			
Gravitas x Minimum investment				-0.041		
				(-2.27)		
Minimum investment				0.020		
				(7.57)		
Gravitas x Bull					-0.032	
					(-2.20)	
Bull					-0.007	
					(-1.07)	
Gravitas x Late						-0.025
						(-3.91)
Late						-0.087
						(-4.90)
Lagged size	-0.020	-0.018	-0.019	-0.020	-0.019	-0.019
	(-42.49)	(-24.42)	(-42.46)	(-41.41)	(-42.47)	(-42.45)
Lagged age	-0.005	-0.006	-0.006	-0.006	-0.006	-0.006
	(-19.26)	(-33.60)	(-33.50)	(-31.67)	(-33.52)	(-33.69)
Restriction	0.013	0.014	0.012	0.010	0.014	0.015
	(4.86)	(4.95)	(3.32)	(3.39)	(5.04)	(5.28)
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes
AdjR2	10.1 %	10.1 %	10.1 %	10.0 %	10.1 %	10.1 %
N	284,975	284,975	284,975	259,968	284,975	284,975