Do Alpha Males Deliver Alpha? Facial Structure and Hedge Funds

Yan Lu and Melvyn Teo*

Abstract

Facial structure, as encapsulated by facial width-to-height ratio (fWHR), maps into a variety of masculine behaviors. We find that high-fWHR hedge fund managers significantly underperform low-fWHR hedge fund managers after adjusting for risk. Moreover, high-fWHR managers are more likely to terminate their funds, disclose violations on their Form ADVs, and exhibit greater operational risk. We trace the underperformance to high-fWHR managers' preference for lottery-like stocks and reluctance to sell loser stocks. The results are robust to adjustments for sample selection, marital status, sensation seeking, biological age, and manager race. Our results suggest that investors should eschew masculine managers.

*Lu is at the College of Business Administration, University of Central Florida. E-mail: yan.lu@ucf.edu. Teo (corresponding author) is at the Lee Kong Chian School of Business, Singapore Management University. Address: 50 Stamford Road, Singapore 178899. E-mail: melvynteo@smu.edu.sg. Tel: +65-6828-0735. Fax: +65-6828-0427. We have benefitted from conversations with Stephen Brown, Chris Clifford (AFA discussant), Lauren Cohen, Fangjian Fu, Aurobindo Ghosh, Jianfeng Hu, Juha Joenväärä (FMA discussant), Matti Keloharju, Andy Kim, Weikai Li, Roger Loh, Roni Michaely, Sugata Ray, Rik Sen, Mandy Tham, Wing Wah Tham, Chishen Wei, and Yachang Zeng, as well as seminar participants at Singapore Management University, University of Central Florida, University of New South Wales, the 2018 Financial Management Association Meetings in San Diego, and the 2019 American Finance Association Meetings in Atlanta. Antonia Kirilova, Jinxing Li, and Aakash Patel provided excellent research assistance. Teo acknowledges support from the Singapore Ministry of Education (MOE) Academic Research Tier 2 grant with the MOE's official grant number MOE 2014-T2-1-174.

1. Introduction

Facial structure as encapsulated by facial width-to-height ratio (henceforth fWHR) – the distance of the bizogymatic width divided by the distance between the brow and the lip – maps into a number of behavioral traits among males. It has been linked to alpha status (Lefevre et al., 2014), aggression (Carré and McCormick, 2008; Carré, McCormick, and Mondloch, 2009), competitiveness (Tsujimura and Banissy, 2013), physical prowess (Zilioli et al., 2015), effective executive leadership (Wong, Ormiston, and Haselhuhn, 2011), and stronger achievement drive (Lewis, Lefevre, and Bates, 2012). Does facial structure also relate to the performance of investment managers? This important question has received short shrift in the literature despite the assets managed by investment managers globally as well as the aggression and competitiveness observed on trading floors (Mallaby, 2010; McDowell, 2010; Riach and Cutcher, 2014). In this study, we seek to fill this gap by analyzing the relation between fWHR and investment performance for 2,744 male hedge fund managers over a 22-year sample period.

The hedge fund industry is a compelling laboratory for exploring the impact of facial structure on investment management. The high-octane and relatively unconstrained strategies that hedge funds employ, which often involve short sales, leverage, and derivatives may appeal to high-fWHR managers given their aggressive (Carré and McCormick, 2008; Carré, McCormick, and Mondloch, 2009) nature. Some high-fWHR managers may also be drawn to the industry's limited transparency and regulatory oversight, which imply opportunities for deception and unethical behavior (Haselhuhn and Wong, 2012; Geniole et al., 2014). Moreover, anecdotal evidence suggests that in the male-dominated hedge fund industry, attributes positively associated with fWHR, such as aggression, competitiveness, and physical prowess, are often synonymous with professional success (Mallaby, 2010; Riach and Cutcher, 2014).[1]

[1]For example, Steve Cohen of SAC Capital and Point72 Asset Management has been described by ex-employees as a driven, aggressive, and ruthless trader. See "Inside SAC's shark tank," Alpha, 1 March

Our analysis reveals substantial differences in expected returns, on decile portfolios of hedge funds sorted by fund manager fWHR, that are unexplained by the Fung and Hsieh (2004) seven factors. Hedge funds managed by managers with high fWHR underperform those managed by managers with low fWHR by an economically and statistically significant 5.83% per year (t-statistic = 3.36) after adjusting for risk. The results are not confined to the smallest funds in our sample and cannot be explained by differences in share restrictions and illiquidity (Aragon, 2007; Aragon and Strahan, 2012), incentives (Agarwal, Daniel, and Naik, 2009), fund age (Aggarwal and Jorion, 2010), fund size (Berk and Green, 2004), return smoothing behavior (Getmansky, Lo, and Makarov, 2004), backfill and incubation bias (Liang, 2000; Fung and Hsieh, 2009; Bhardwaj, Gorton, and Rouwenhorst, 2014), and manager manipulation of fund returns (Agarwal, Daniel, and Naik, 2011; Aragon and Nanda, 2017). The results therefore indicate that facial structure can have implications for investment performance.

Why do high-fWHR fund managers underperform? We show that facial structure can shape trading behavior and lead to sub-optimal decisions. We find that high-fWHR fund managers trade more frequently, have a stronger preference for lottery-like stocks, and are more likely to succumb to the disposition effect. These findings are broadly consistent with prior studies that show that fWHR is associated with aggressiveness (Carré and McCormick, 2008; Carré, McCormick, and Mondloch, 2009) and competitiveness (Tsujimura and Banissy, 2013).[2] We show further that, in line with the findings of Barber and Odean (2000, 2001), Bali, Cakici, and Whitelaw (2011), and Odean (1998), the high turnover, preference for lottery-like stocks, and reluctance to sell loser stocks of high-fWHR managers in turn engenders underperformance.

2010. Julian Robertson of Tiger Management was tall, confident, and athletic, and hired in his own image. According to Mallaby (2010), "to thrive at Robertson's Tiger Management, you almost needed the physique; otherwise you would be hard-pressed to survive the Tiger retreats, which involved vertical hikes and outward bound contests in Idaho's Sawtooth Mountains." Jim Chanos of Kynikos Associates bench-presses an impressive 300lbs. See "Jim Chanos on bench-pressing, short selling, and the importance of immigration," Square Mile, 12 October 2017.

[2]Competitiveness may be related to the disposition effect as competitive individuals could simply hate to lose and therefore be more averse to losses.

Do high-fWHR fund managers take on greater risk? Haselhuhn and Wong (2012) and Geniole et al. (2014) show that fWHR predicts unethical behavior among men. In the hedge fund context, unethical behavior can lead to greater operational risk. In line with this view, we find that hedge fund managers with high fWHR are more likely to disclose regulatory actions as well as civil and criminal violations on their Form ADVs. They are also more likely to terminate their funds.[3] Moreover, hedge funds managed by high-fWHR managers exhibit higher ω-Scores, a univariate measure of operational risk (Brown et al., 2009). These results suggest that high-fWHR managers may be more predisposed to fraud (Dimmock and Gerken, 2012). We show also that, unlike the sensation-seeking managers studied in Brown et al. (2018), high-fWHR managers do not take on more financial risk.

Why do hedge fund investors subscribe to high-fWHR hedge funds given their lower alphas and higher operational risk? We leverage on return data from funds of hedge funds (henceforth FoFs) to show that hedge fund investors are themselves affected by facial structure and that investors select into high- versus low-fWHR hedge funds based on their own fWHR levels. In particular, FoFs operated by managers with high fWHR underperform those operated by managers with low fWHR by 4.53% per year (t-statistic = 2.27) after adjusting for risk. Moreover, relative to other FoFs, high-fWHR (low-fWHR) FoFs load most on high-fWHR (low-fWHR) hedge funds. One view is that the aggressive trading style of high-fWHR hedge fund managers appeals to high-fWHR investors as it mirrors their own.

Since high-fWHR investors are drawn to high-fWHR managers, and fWHR is positively related to active trading, we posit that the flows into high-fWHR hedge funds are more responsive to past fund performance as high-fWHR investors trade their hedge fund portfolios more actively. This is precisely what we find. Flows into high-fWHR hedge funds are significantly more sensitive to past fund performance than are flows into low-fWHR hedge funds, thereby suggesting that fWHR is linked to heighten fund flow-performance sensitivity.

We show that incentive alignment attenuates the relation between facial structure and

[3] Brown et al. (2009) find that operational risk is even more significant than financial risk in explaining fund failure.

underperformance, but only when fund managers cannot autonomously influence the alignment mechanism itself. For example, the relation between fWHR and performance is weaker for funds that are operating closer to their high-water marks, i.e., those with higher manager total deltas (Agarwal, Daniel, and Naik, 2009). However, we do not observe a similar effect for funds with manager co-investment (Brown et al., 2009). This is because high-fWHR managers, for whom the fWHR-performance relation is strongest, tend to co-invest personal capital in their funds to aggressively increase their pay-performance sensitivity.

Our results flow from the behavioral traits such as aggression, competitiveness, and deceptiveness that relate to fWHR. What is the underlying biological mechanism that links facial structure to those behavioral traits? The *circulating testosterone* hypothesis postulates that fWHR positively relates to baseline and reactive testosterone levels in men. Consistent with this hypothesis, Lefevre et al. (2013) show that fWHR has a positive correlation with saliva-assayed testosterone for men before and after potential mate exposure via a speed-dating event. However, this hypothesis is still open to debate in the neuroendocrinology literature. For example, Bird et al. (2016) find in their meta analysis that there is no significant positive relationship between fWHR and baseline testosterone, or between fWHR and three measures of competition-induced testosterone reactivity.[4] To investigate the *circulating testosterone* hypothesis, we redo our baseline regressions with two alternative biomarkers for salivary testosterone documented by Lefevre et al. (2013): face width-to-lower face height and lower face height-to-whole face height. Consistent with the *circulating testosterone* hypothesis, we find that managers with higher values of face width-to-lower face height and smaller values of lower face height-to-whole face height also underperform.[5] The *pubertal testosterone* hypothesis on the other hand, posits that fWHR's association with certain be-

[4]The dissonance between Bird et al. (2016) and Lefevre et al. (2013) may stem from two factors. First, Lefevre et al. (2013) analyze testosterone post potential mate exposure while Bird et al. (2016) study testosterone after competitions that typically involve video games. Second, Lefevre et al. (2013) control for age and body mass index in their analysis of fWHR and testosterone while Bird et al. (2016) do not.

[5]Lefevre et al. (2013) report that face width-to-lower face height is positively related while lower face height-to-whole face height is negatively related to post-exposure testosterone for men. See their Table 2. Since the computation of lower face height-to-whole face height does not involve facial width, these results help sidestep concerns that facial adiposity or fat may be responsible for our findings.

havioral traits are tied to exposure to testosterone in puberty, rather than to baseline or reactive testosterone in adulthood (Weston, Friday, and Liò, 2007). Consistent with this hypothesis, research has shown that testosterone during adolescence influences both craniofacial growth (Verdonck et al., 1999; Nie, 2005; Lindberg et al., 2005) and the development of neural circuitry (Vigil et al., 2016). Moreover, Mehta and Beer (2009) provide a neural basis for the effect of testosterone on behavior. While the *pubertal testosterone* hypothesis has been challenged by Hodges-Simeon et al. (2016), it has also found support in the results of Welker, Bird, and Arnocky (2016).[6] Nevertheless, given the uncertainty surrounding these hypotheses, we approach the link between fWHR and testosterone with caution.

Regardless of the underlying biological mechanism at work, the findings in this paper challenge the neoclassical view that manager facial structure should not matter for fund performance. In doing so, we resonate with work on hedge fund performance. This literature finds that motivated (Agarwal, Daniel, and Naik, 2009), geographically proximate (Teo, 2009), emerging (Aggarwal and Jorion, 2010), low R^2 (Titman and Tiu, 2011), and distinctive (Sun, Wang, and Zheng, 2012) hedge funds outperform, as do those with low volatility of aggregate volatility exposure (Agarwal, Arisoy, and Naik, 2017). We show that those operated by managers with lower fWHR also outperform.[7]

This paper deepens our understanding of the sources of hedge fund operational risk. Work on hedge fund operational risk has focused on assessing operational risk and its impact (Brown et al., 2008; 2009; 2012) or predicting hedge fund fraud, one instance of operational risk (Dimmock and Gerken, 2012; Bollen and Pool, 2012). We show that facial structure may be an underlying driver of operational risk in hedge funds.

We contribute to an emerging literature that examines the impact of facial structure

[6] Specifically, Hodges-Simeon et al. (2016) find little evidence that fWHR is related to pubertal testosterone in a sample of 75 Tsimane males from the Bolivian Amazon and with a liberal criterion for adolescence (i.e., ages 8–22 years). Welker, Bird, and Arnocky (2016), however, document a strong and positive relation between fWHR and testosterone exposure based on the Hodges-Simeon et al. (2016) data after controlling for age and limiting the sample to adolescent males who were between 12–16 years old.

[7] Our work is also related to studies on how the personal characteristics of fund managers such as college SAT scores (Chevalier and Ellison, 1999; Li, Zhang, and Zhao, 2011), relative age (Bai et al, 2019) and Ph.D. training (Chaudhuri et al, 2019) affect investment performance.

on financial outcomes.[8] It finds that Chief Executive Officers (henceforth CEOs) with high fWHR deliver higher return on assets (Wong, Ormiston, and Haselhuhn, 2011), are more likely to engage in financial misreporting (Jia, van Lent, and Zeng, 2014), and take on more risk (Kamiya, Kim, and Park, 2019). Our results on Form ADV violations echo those of Jia, van Lent, and Zeng (2014) while our findings on the underperformance of high-fWHR managers contrast with those of Wong, Ormiston, and Haselhuhn (2011). The dissonance suggests that fWHR, while helpful for executive leadership, is detrimental to investment management.[9]

Insofar as fWHR is positively linked to testosterone, our findings also contribute to work on testosterone and individual investor trading behavior. Research in this area has shown in experimental settings that high-testosterone men overbid for assets (Nadler et al., 2018) and take on more risk (Apicella et al., 2008). In addition, Cronqvist et al. (2016) show that among fraternal twins, females with higher prenatal testosterone exposure invest more in equities, hold more volatile portfolios, trade more often, and load more on lottery-like stocks than do females with lower prenatal testosterone exposure. However, none of these papers investigate investment performance. Our work is related to Coates and Herbert (2008) and Coates, Gurnell, and Rustichini (2009) who show that high-testosterone intraday traders outperform. Nonetheless, it is difficult to generalize their results to investment management given their limited sample sizes (17 and 44 traders, respectively) and the fact that the skills prized in intraday or noise trading, i.e., rapid visuomotor scanning abilities and sharp physical reflexes, may not be relevant for the more analytical forms of trading commonly employed by asset managers.[10] Moreover, they do not control for risk in their analysis of

[8] In a related work, He et al. (2019) find that high-fWHR sell-side analysts in China make more accurate forecasts. They ascribe their findings to the stronger achievement drive among high-fWHR analysts. Our results suggest that stronger achievement drive may be counterproductive when taking risk in financial markets. Our findings also resonate with work by Harlow and Brown (1990), Kuhnen and Knutson (2005), and Cesarini et al. (2009; 2010) that link biological metrics to financial decision making.

[9] In an auxiliary test, we find that the negative relation between fWHR and fund performance is driven by managers who are Chief Investment Officers and Portfolio Managers, and not by those who are CEOs.

[10] For example, unlike the intraday traders in the aforementioned studies, who typically hold their positions for only a few minutes, sometimes mere seconds, hedge fund managers often take more time to analyze their positions and hold their trades for weeks, months, and even years (Perold, 2003; Cohen and Sandbulte,

investment performance. Our results suggest that testosterone, to the extent that it is linked to fWHR, is not helpful for the more analytical forms of trading that hedge funds generally engage in. These findings are consistent with those of Reavis and Overman (2001), van Honk et al. (2004), and Nave et al. (2017) who show in laboratory settings that testosterone can lead individuals to make irrational risk-reward tradeoffs.

This study therefore enriches the nascent literature on manager facial structure in finance in the following ways. First, we present novel results on the relation between fWHR and investment performance. Our findings on the underperformance of high-fWHR hedge fund managers offer fresh insights relative to prior studies on intraday traders. The results are important in light of the over US$3 trillion of assets managed by the hedge fund industry and may have implications for investment management in general.[11] Second, while we do not find that high-fWHR hedge fund managers take on more financial risk, we find that they exhibit greater operational risk, are more likely to fail, and disclose more regulatory, civil, and criminal violations. Investors are not compensated for taking operational risk. Therefore, these findings are helpful for investors as they seek to minimize operational risk and avoid fraud. Third, we show that facial structure can underlie behavioral biases such as the disposition effect. Fourth, our findings on how high-fWHR investors subscribe more to hedge funds operated by high-fWHR managers help us understand why high-fWHR managers can persist in the financial ecosystem. Fifth, we show that manager facial width is associated with heightened flow-performance sensitivity.

In our work, we carefully consider several alternative explanations, including sample selection, marital status (Love, 2010; Roussanov and Savor, 2014), biological age, limited attention, manager race, barriers to entry, and fund management company fixed effects, but find that they are unlikely to drive our findings. Our results are also not driven by sensation seeking (Grinblatt and Keloharju, 2009; Brown et al., 2018). Unlike the sensation seekers

2006).

[11]According to BarclayHedge, hedge funds collectively managed over US$3 trillion in assets in the third quarter of 2018. See https://www.barclayhedge.com/solutions/assets-under-management/hedge-fund-assets-under-management/

studied in Brown et al (2018), high-fWHR managers do not take on more financial risk. We show that while sensation seekers are quick to realize losses, high-fWHR managers tend to hold on to their loser stocks. More importantly, our baseline results are even stronger after controlling for sensation seeking via speeding tickets (Grinblatt and Keloharju, 2009) or via sports car ownership (Brown et al., 2018).

The remainder of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 reports the empirical results. Section 4 discusses alternative explanations. Section 5 presents robustness tests while Section 6 concludes.

2. Data and methodology

We evaluate the impact of manager facial structure on hedge funds using monthly net-of-fee returns and assets under management (henceforth AUM) data of live and dead hedge funds reported in the Lipper TASS, Morningstar, Hedge Fund Research (henceforth HFR), and BarclayHedge data sets from January 1990 to December 2015. Because TASS, Morningstar, HFR, and BarclayHedge started distributing their data in 1994, the data sets do not contain information on funds that died before January 1994. This gives rise to survivorship bias. We mitigate this bias by focusing on data from January 1994 onward.

In our fund universe, we have a total of 49,672 hedge funds, of which 28,810 are live funds and 20,862 are dead funds. However, due to concerns that funds with multiple share classes could cloud the analysis, we exclude duplicate share classes from the sample. This leaves a total of 26,945 hedge funds, of which 16,929 are live funds and 10,016 are dead funds. The funds are roughly evenly split between Lipper TASS, Morningstar, HFR, and BarclayHedge. While 6,652 funds appear in multiple databases, many funds belong to only one database. Specifically, there are 6,594, 3,267, 5,221, and 4,578 funds unique to the Lipper TASS, Morningstar, HFR, and BarclayHedge databases, respectively. This highlights the advantage of obtaining data from more than one source.

For each male manager in the combined database, we use manager first name, manager last name, and fund management company name to perform a Google image search for the manager's facial picture or pictures. If we find more than one picture of the manager, we identify the best photograph in terms of resolution, whether the manager is forward facing, and whether he has a neutral expression. We follow Carré and McCormick (2008) and manually measure fWHR using the ImageJ software provided by the National Institute of Health (Rasband, 2018). As per Carré and McCormick (2008), we define the measure as the distance between the two zygions (bizygomatic width) relative to the distance between the upper lip and the midpoint of the inner ends of the eyebrows (height of the upper face).[12]

In total, we are able to obtain valid photos and compute fWHRs for 2,744 male fund managers. These managers operate 3,152 hedge funds and belong to 1,633 fund management companies. We define fund fWHR as the average fWHR of the managers running a hedge fund. In this study, we use fund fWHR as a proxy of the level of manager fWHR associated with a hedge fund.[13]

Following Agarwal, Daniel, and Naik (2009), we classify funds into four broad investment styles: Security Selection, Multi-process, Directional Trader, and Relative Value. Security Selection funds take long and short positions in undervalued and overvalued securities, respectively. Usually, they take positions in equity markets. Multi-process funds employ multiple strategies that take advantage of significant events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. Directional Trader funds bet on the direction of market prices of currencies, commodities, equities, and bonds in the futures and cash markets. Relative Value funds take positions on spread relations between prices of financial assets and aim to minimize market exposure.

[12]See Fig. 1 in Carré and McCormick (2008). Some researchers (Lefevre et al., 2013; Jia, van Lent, and Zeng, 2014) measure the height of the upper face as the distance between the upper lip and the top of the eyelids. The advantage of our approach is that it better measures facial bone structure. We acknowledge that, despite our best efforts, the measurement of fWHR is not perfect. The resultant measurement error makes it harder for us to find statistical significance in our empirical tests.

[13]Our results are robust when we analyze only hedge funds with one manager. In those cases, fund fWHR equals manager fWHR.

Table 1 reports the distribution of hedge fund manager fWHR and hedge fund fWHR by investment strategy. The average manager fWHR is 1.823 with a standard deviation of 0.165. Similarly, the average fund fWHR is 1.825 with a standard deviation of 0.150. We observe little evidence that high-fWHR hedge fund managers gravitate to specific investment styles. The average fWHR in our hedge fund manager sample agrees well with that found in the prior literature. For example, Carré and McCormick (2008) report an average fWHR of 1.860 for their sample of 37 male undergraduates. See their Table 1. We also note that the hedge fund managers in our sample have lower fWHRs than do public company CEOs. For example, Jia, van Lent and Zeng (2014) report an average CEO fWHR of 2.013 (standard deviation = 0.149) while Kamiya, Kim, and Park (2019) report an average CEO fWHR of 2.014 (standard deviation = 0.154). This provides prima facie evidence that a higher fWHR may be less beneficial for fund managers than it is for firm CEOs.

[Insert Table 1 here]

Hedge fund data are susceptible to many biases (Fung and Hsieh, 2009). These biases stem from the fact that inclusion in hedge fund databases is voluntary. As a result, there is a self-selection bias. For instance, when a fund is listed on a database, it often includes data prior to the listing date. Because successful funds have a strong incentive to list and attract capital, these backfilled returns tend to be higher than the non-backfilled returns. To alleviate concerns about backfill bias raised by Bhardwaj, Gorton, and Rouwenhorst (2014), and others, we rerun the tests after removing all return observations that have been backfilled prior to the fund listing date.

Throughout this paper, we model the risk of hedge funds using the Fung and Hsieh (2004) seven-factor model. The Fung and Hsieh factors are the excess return on the Standard and Poor's (S&P) 500 index (SNPMRF); a small minus big factor (SCMLC) constructed as the difference between the Russell 2000 and S&P 500 stock indexes; the yield spread of the U.S. ten-year Treasury bond over the three-month Treasury bill, adjusted for duration of the ten-year bond (BD10RET); the change in the credit spread of Moody's BAA bond over the ten-year Treasury bond, also appropriately adjusted for duration (BAAMTSY); and the excess returns on portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD), which are constructed to replicate the maximum possible return from trend-following strategies on their respective underlying assets.[14] Fung and Hsieh (2004) show that these seven factors have considerable explanatory power on aggregate hedge fund returns.

3. Empirical results

3.1. Fund performance

To begin, we test for differences in risk-adjusted performance of funds sorted by fund fWHR. Every year, starting in January 1994, ten hedge fund portfolios are formed by sorting funds on the average fWHR of the managers managing the fund, i.e., fund fWHR. The post-formation returns on these ten portfolios over the next 12 months are linked across years to form a single return series for each portfolio. We then evaluate the performance of the portfolios relative to the Fung and Hsieh (2004) model.

The results, reported in Panel A of Table 2, reveal substantial differences in expected returns, on the portfolios sorted by fund fWHR, that are unexplained by the Fung and Hsieh (2004) seven factors. Hedge funds managed by managers with high fWHR underperform those managed by managers with low fWHR by an economically and statistically significant 6.14% per year (t-statistic = 2.23). After adjusting for co-variation with the Fung and Hsieh (2004) factors, the underperformance decreases marginally to 5.83% per year (t-statistic = 3.36).[15] As in the rest of the paper, we base statistical inferences on White (1980) heteroskedasticity-consistent standard errors. We note that the average fWHR for

[14] David Hsieh kindly supplied these risk factors. The trend-following factors can be downloaded from http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-Fac.xls.

[15] The portfolio sort results are robust to value-weighting the funds within each portfolio. The risk-adjusted spread for the value-weighted sort is 7.56% per annum (t-statistic = 2.00).

the high-fWHR funds in Portfolio 1 is 2.12 while that for the low-fWHR funds in Portfolio 10 is 1.61.

Since hedge funds with investor capital below US$20 million may not be relevant to large institutional investors, we also conduct the portfolio sort on the sample of hedge funds with at least US$20 million of AUM. The results reported in Panel B of Table 2 indicate that our findings are not driven by small funds. After removing funds with AUM less than US$20 million, the outperformance of low-fWHR funds over high-fWHR funds is only marginally lower at 5.64% per annum (t-statistic = 3.78) after adjusting for risk.

[Insert Table 2 and Fig. 1 here]

Fig. 1 complements the results from Panel A of Table 2. It illustrates the monthly cumulative abnormal returns (henceforth CARs) from the portfolio of high-fWHR funds (portfolio 1) and the portfolio of low-fWHR funds (portfolio 10). High-fWHR funds are those in the top decile based on fund fWHR while low-fWHR funds are those in the bottom decile based on fund fWHR. CAR is the cumulative difference between a portfolio's excess return and its factor loadings (estimated over the entire sample period) multiplied by the Fung and Hsieh (2004) risk factors. The CARs in Fig. 1 indicate that the high-fWHR fund portfolio consistently underperforms the low-fWHR fund portfolio over the entire sample period and suggest that the underperformance of funds managed by high-fWHR managers is not peculiar to a particular year.

To further test the explanatory power of manager facial structure on fund performance, we estimate the following pooled OLS regression:

$$\begin{aligned} ALPHA_{im} = {} & \alpha + \beta_1 FWHR_i + \beta_2 MGTFEE_i + \beta_3 PERFFEE_i \\ & + \beta_4 HWM_i + \beta_5 LOCKUP_i + \beta_6 LEVERAGE_i + \beta_7 AGE_{im-1} \\ & + \beta_8 REDEMPTION_i + \beta_9 log(FUNDSIZE_{im-1}) \\ & + \sum_k \beta_{10}^k STRATEGYDUM_i^k + \sum_l \beta_{11}^l YEARDUM_m^l + \epsilon_{im}, \end{aligned} \tag{1}$$

where *ALPHA* is fund monthly abnormal return after stripping away co-variation with the Fung and Hsieh (2004) seven factors, *FWHR* is fund fWHR or manager fWHR averaged across the managers in the fund, *MGTFEE* is management fee, *PERFFEE* is performance fee, *HWM* is high watermark indicator, *LOCKUP* is lock-up period, *LEVERAGE* is leverage indicator, *AGE* is fund age since inception, *REDEMPTION* is redemption period, log(*FUNDSIZE*) is the natural logarithm of fund AUM, *STRATEGYDUM* is the fund strategy dummy, and *YEARDUM* is the year dummy. Fund alpha is monthly abnormal return from the Fung and Hsieh (2004) model, where the factor loadings are estimated over the prior 24 months.[16] We also estimate the analogous regression on raw monthly fund returns to ensure that our findings are not artefacts of the risk adjustment methodology. We base statistical inferences on White (1980) robust standard errors clustered by fund and month.

[Insert Table 3 here]

The results from the regression analysis, reported in columns (1) and (2) of Table 3, corroborate the findings from the portfolio sorts. Specifically, the coefficient estimate on *FWHR* in the alpha regression reported in column (2) of Table 3 indicates that, controlling for other factors that could explain fund performance, high-fWHR funds (fWHR = 2.12) underperform low-fWHR funds (fWHR = 1.61) by 2.30% per annum (t-statistic = 3.35) after adjusting for risk. The results reported in column (1) of Table 3 indicate that inferences do not change when we estimate the regression on raw returns suggesting that our prior findings are not driven by our risk adjustment technology. The coefficient estimates on the control variables accord with the extant literature. Longer redemption notice periods and lock-up periods (Aragon, 2007) are associated with superior performance, while fund age (Aggarwal and Jorion, 2010) is linked to poorer performance. The impact of fund size on performance is more ambiguous. While size is associated with lower returns (Berk and Green, 2004), it is also linked to higher alphas.

[16] Inferences do not change when we use factor loadings estimated over the past 36 months to calculate alpha instead.

To check for robustness, we rerun the baseline return and alpha regressions with *FWHR_RANK* in place of *FWHR*. The variable *FWHR_RANK* is simply the fund fWHR fractional rank determined every month based on funds that report returns that month. It takes values from zero to one. The results reported in columns (3) and (4) of Table 3 indicate that our baseline findings are robust to alternative specifications.

We also estimate analogous regressions on *SHARPE* and *INFORMATION*, where *SHARPE* is fund Sharpe ratio or average monthly excess returns divided by standard deviation of monthly returns over a 24-month period, and *INFORMATION* is fund information ratio or average monthly abnormal returns divided by standard deviation of fund residuals over a 24-month period. Fund abnormal returns and residuals are determined relative to the Fung and Hsieh (2004) model. Both *SHARPE* and *INFORMATION* are computed for all nonoverlapping 24-month periods post fund inception. We base statistical inferences on robust standard errors that are clustered by fund. An advantage of analyzing fund Sharpe ratio and information ratio is that, unlike fund alpha, they are invariant to fund leverage. The results reported in columns (5) to (8) of Table 3 indicate that manager facial width is associated with lower Sharpe ratios and information ratios. Specifically, high-fWHR funds (fWHR = 2.12) deliver annualized Sharpe ratios that are 0.65 (t-statistic = 5.87) lower than do low-fWHR funds (fWHR = 1.61).

3.2. Fund trading behavior

How does manager facial structure engender fund underperformance? One view is that since fWHR correlates positively with aggression (Carré and McCormick, 2008; Carré, McCormick, and Mondloch, 2009), risk-seeking (Kamiya, Kim, and Park, 2019), and competitiveness (Tsujimura and Banissy, 2013), high-fWHR managers may turn their portfolios over more often, load more on lottery-like stocks, be more susceptible to behavioral biases such as the disposition effect, and trade stocks more actively? The extant finance literature has shown that higher turnover (Barber and Odean, 2000; 2001), a preference for lotteries

(Kumar, 2009; Bali, Cakici, and Whitelaw, 2011), and the disposition effect (Odean, 1998) can hurt investment performance. In this section, we investigate how facial structure can shape manager trading behavior and thereby influence investment performance.

In that effort, we construct five trading behavior metrics from hedge fund 13-F long-only quarterly stock holdings: *TURNOVER*, *LOTTERY*, *DISPOSITION*, *NONSPRATIO*, and *ACTIVESHARE*. The metric *TURNOVER* is the annualized turnover of a hedge fund manager's stock portfolio. *LOTTERY* is the maximum daily stock return over the past month averaged across stocks held by the fund. Bali, Cakici, and Whitelaw (2011) argue that stocks with high maximum daily return over the past month capture investor preference for lottery-like stocks. *DISPOSITION* is the difference between the percentage of gains realized and the percentage of losses realized as per Odean (1998). *NONSPRATIO* is the ratio of the number of non-S&P 500 index stocks bought in a quarter to the total number of new positions in the quarter. *ACTIVESHARE* is Active Share as defined in Cremers and Petajisto (2009) relative to the S&P 500. The last two measures capture active trading.

[Insert Table 4 here]

Next, we estimate multivariate regressions on the trading behavior metrics with the set of controls used in Eq. (1). The results reported in Table 4 indicate that fund fWHR is associated with higher turnover (although the effect is only statistically significant at the 10% level), a preference for lottery-like stocks, a tendency to succumb to the disposition effect, and active trading. Does such trading behavior in turn engender the underperformance of high-fWHR hedge fund managers? To investigate, we estimate the Eq. (1) performance regressions but with the trading behavior metrics computed in the previous quarter in place of *FWHR*. We find in results reported in Table A1 of the Internet Appendix that consistent with the findings of Barber and Odean (2000), Bali, Cakici, and Whitelaw (2011), and Odean (1998), such trading behavior is associated with weaker investment performance.[17]

[17]The finding that higher *ACTIVESHARE* is associated with lower future investment performance for hedge funds differs from those of Cremers and Petajisto (2009) on mutual funds. We note that the relation

3.3. Fund operational risk

The extant literature has shown that fWHR predicts unethical behavior in men (Haselhuhn and Wong, 2012; Geniole et al., 2014). In the hedge fund context, unethical behavior can manifest as increased operational risk. In this section, we explore differences between the operational risk attributes of fund managers with high versus low fWHR by analyzing the cross-sectional determinants of fund termination and other operational risk metrics.

Our analysis of fund termination is motivated by Brown et al. (2009) who find that operational risk is even more significant than financial risk in explaining fund failure. To explore the relation between manager facial structure and fund termination, we estimate a multivariate logit regression on an indicator variable for fund termination with the set of independent variables used in the Eq. (1) regressions. The indicator variable, *TERMINATION*, takes a value of one when a fund stops reporting returns for that month and states that it has liquidated, and takes a value of zero otherwise. We limit the analysis to TASS and HFR funds since only TASS and HFR provide the reason for why a fund stopped reporting returns.

[Insert Table 5 here]

The results reported in column (1) of Table 5 indicate that, controlling for other factors that can explain fund termination, high-fWHR managers are more likely to terminate their funds. The marginal effect from the logit regression suggests that high-fWHR funds (fWHR = 2.12) are 4.12 percentage points more likely to terminate in any given year than are low-fWHR funds (fWHR = 1.61).[18] These results are economically meaningful given that the unconditional probability of fund termination in any given year is 6.17%. As a robustness

between risk-adjusted performance and Active Share is not always robust even for mutual funds. For example, Busse, Jiang, and Tang (2019) show that the significant relation between Active Share and the Carhart (1997) four-factor alpha in mutual funds is driven by the characteristic-related component of performance (Daniel et al., 1997) rather than by fund skill.

[18]The marginal effect reported in column (1) of Table 5 reveals that a one-unit increase in *FWHR* is associated with a 0.7 percentage point increase in the probability of termination in any given month or a $100 * (1 - (1 - 0.007)^{12}) = 8.08$ percentage point increase in probability of termination in any given year.

test, we estimate a semi-parametric Cox hazard rate regression on fund termination. As shown in column (2) of Table 5, inferences remain unchanged when we model fund survival in this way.

Unethical behavior may lead to deviations from expected standards of business conduct that could precipitate regulatory action and lawsuits, as well as civil and even criminal violations. These events must be reported as Item 11 disclosures on Form ADV.[19] To explore the relation between fWHR and violations of expected standards of business conduct, we estimate multivariate logit regressions on an indicator variable for Form ADV violations. The indicator variable *VIOLATION* takes a value of one when a fund manager reports on his Form ADV file that he has been associated with an Item 11 Form ADV disclosure, and a value of zero otherwise. Form ADV includes disclosure on all regulatory actions taken against the fund and lawsuits as well as civil and criminal violations linked to the investment advisor over the past ten years.

Column (3) of Table 5 reports the coefficient estimates and marginal effects from the logit regression on *VIOLATION*. The set of independent variables that we employ is analogous to that used in the baseline Eq. (1) regressions. We find that hedge fund managers with high fWHR are more likely to report on their Form ADVs that they have been associated with past regulatory, civil, and criminal violations. The coefficient estimate on *FWHR* is positive and statistically significant at the 1% level. The marginal effect indicates that funds operated by managers with high fWHR (fWHR = 2.12) are 17.39 percentage points more likely to report a violation on their Form ADVs than are funds operated by managers with low fWHR (fWHR = 1.61).

To further investigate the relation between fWHR and operational risk, we compute fund ω-Score, an operational risk instrument derived from fund performance, volatility, age, size,

[19] For a brief period in 2006, all hedge funds domiciled in the United States and meeting certain minimal conditions had to register as financial advisors and file the necessary Form ADV that provides basic information about the operational characteristics of the fund. This requirement was dropped in June 2006, but since that date, most hedge funds continue to voluntarily file this form, and since the passage of the Dodd Frank Act all hedge funds with over $100M assets under management are required to file this form.

fee structure, and other fund characteristics that Brown et al. (2009) show is useful for predicting hedge fund failures.[20] Next, we estimate a multivariate regression on *OMEGA* or fund ω-Score with *FWHR* as an independent variable. The set of control variables that we employ is analogous to that used in the baseline Eq. (1) regressions. The results reported in column (4) of Table 5 support the view that high-fWHR funds exhibit higher ω-Scores. The coefficient estimate on *FWHR* is positive and statistically significant at the 5% level.

Do high-fWHR hedge funds also take on more investment risk given the link between fWHR and risk-taking for firm CEOs (Kamiya, Kim, and Park, 2019)? To investigate, we estimate analogous regressions on fund risk (*RISK*), idiosyncratic risk (*IDIORISK*), systematic risk (*SYSTEMRISK*), and tail risk (*TAILRISK*). *RISK* is standard deviation of monthly hedge fund returns. *IDIORISK* is the standard deviation of monthly hedge fund residuals from the Fung and Hsieh (2004) seven-factor model. *SYSTEMRISK* is the square root of the difference between the variance of monthly fund returns and that of monthly fund residuals. *TAILRISK* is calculated as per Agarwal, Ruenzi, and Weigert (2017). The risk measures are estimated over each nonoverlapping 24-month period post fund inception. The results reported in Table A2 of the Internet Appendix indicate that unlike the sensation seekers studied in Brown et al. (2018), high-fWHR hedge fund managers do not take on more risk. The coefficient estimates on *FWHR* are statistically indistinguishable from zero at the 10% level for all measures of risk.

3.4. Fund investors

Why do hedge fund investors subscribe to high-fWHR hedge funds given their lower alphas and higher operational risk? One view is that hedge fund investors are themselves affected by facial structure and that investors select into high- versus low-fWHR hedge funds based

[20]The ω-Score is based on a canonical correlation analysis that related a vector of responses from Form ADV to a vector of fund characteristics in the TASS database, across all hedge funds that registered as investment advisors in the first quarter of 2006. The fund characteristics used include fund manager personal capital. See Table 3 in Brown et al. (2009) for the list of TASS fund characteristics used. Since only TASS provides information on fund manager personal capital, we only compute the ω-Score for TASS funds, as per Brown et al. (2009).

on their own fWHR levels. In this section, we investigate this hypothesis by analyzing return data on funds of hedge funds (FoFs). Our FoF sample includes 573 FoFs managed by 397 male FoF managers for whom we are able to compute fWHRs.

To test whether investors are themselves affected by facial structure, we evaluate differences in risk-adjusted performance of FoFs sorted by fund fWHR. As in the baseline portfolio sort for hedge funds, every year, starting in January 1994, ten FoF portfolios are formed by sorting FoFs on the average fWHR of the managers managing the fund. The post-formation returns on these ten FoF portfolios over the next 12 months are linked across years to form a single return series for each FoF portfolio. We then evaluate the performance of the FoF portfolios relative to the Fung and Hsieh (2004) model.

The results, reported in Table 6, reveal substantial differences in expected returns, on the FoF portfolios sorted by fund fWHR. FoFs managed by managers with high fWHR underperform those managed by managers with low fWHR by an economically and statistically significant 4.39% per year (t-statistic = 1.97). After adjusting for co-variation with the factors from the Fung and Hsieh (2004) model, the magnitude of the underperformance increases marginally to 4.53% per year (t-statistic = 2.27). These results indicate that fund investors are themselves affected by fWHR.

[Insert Tables 6 and 7 here]

To test whether high-fWHR investors gravitate toward high-fWHR hedge fund managers, we estimate regressions on the excess returns of FoF portfolios sorted by manager fWHR with excess returns of hedge fund portfolios sorted by manager fWHR as independent variables. Specifically, every January 1st, we stratify FoFs into high-, medium-, and low-fWHR FoFs. High- and low-fWHR FoFs are FoFs in the top 30th and bottom 30th percentiles, respectively, based on fund fWHR. Medium-fWHR FoFs are FoFs with fund fWHR that lie above the 30th percentile and below the 70th percentile. High-, medium- and low-fWHR hedge funds are defined analogously. Next, we estimate time-series regressions on the excess returns from these FoF portfolios with the excess returns of these hedge fund portfolios as independent variables.[21]

The results reported in Panel A of Table 7 are consistent with the view that investors select into high- versus low-fWHR hedge funds based on their own fWHR levels. Relative to other hedge funds, high-fWHR FoFs load most on high-fWHR hedge funds. Similarly, relative to other hedge funds, low-fWHR FoFs load most on low-fWHR hedge funds. Moreover, high-fWHR FoFs load more on high-fWHR hedge funds and less on low-fWHR hedge funds than do low-fWHR FoFs. The loading on the high-fWHR hedge fund portfolio for the high- versus low-fWHR FoF spread is positive and statistically significant at the 1% level, while that on the low-fWHR hedge fund portfolio is negative and statistically significant at the 1% level.

One concern is that the results may be driven by potentially similar risk factor loadings of high-fWHR FoFs and hedge funds. To address this concern, we reestimate the time-series regressions after controlling for co-variation with the Fung and Hsieh (2004) seven factors. The coefficient estimates reported in Panel B of Table 7 indicate that our results are qualitatively unchanged after accounting for risk.

3.5. Fund flow-performance sensitivity

Do high-fWHR investors also trade more actively by engaging in positive feedback trading (Agarwal, Green, and Ren, 2018), thereby engendering greater flow-performance sensitivity for the high-fWHR hedge funds that they subscribe to? To test, we first classify high- and low-fWHR funds as those with fund fWHR in the top and bottom 30th percentiles, respectively. Next, we estimate multivariate regressions on hedge fund annual flow with fund performance rank based on past one-year return ($RANK$) as the independent variable of interest as in Siri and Tufano (1998). We also control for the set of fund characteristics featured in the Eq. (1) regression, and for investment style and year fixed effects. The

[21]Our results are robust to re-classifying high- and low-fWHR FoFs as those with fund fWHR in the top 10th and bottom 10th percentiles, respectively.

regressions are estimated separately for high- and low-fWHR funds.

The results reported in Table 8 indicate that flows into high-fWHR hedge funds are indeed more sensitive to past performance than are flows into low-fWHR hedge funds. The coefficient estimate on $RANK$ for high-fWHR hedge funds is large, positive, and statistically significant at the 1% level. Conversely, that for low-fWHR hedge funds is economically modest and statistically indistinguishable from zero. Further, when we estimate analogous regressions on both high- and low-fWHR hedge funds and include a dummy for high-fWHR funds as well as the interaction of the dummy with $RANK$, we find that the coefficient estimate on the interaction variable is positive and statistically significant at the 5% level. To check for robustness, we rerun the flow regressions with fund performance rank based on past one-year CAPM alpha ($RANK\_CAPM$) or on past one-year Fung and Hsieh (2004) alpha ($RANK\_FH$), and obtain qualitatively similar results.[22] Collectively, these results echo our findings on hedge fund manager trading behavior and suggest that high-fWHR investors trade their hedge fund portfolios more actively than do low-fWHR investors. By doing so, high-fWHR investors foment greater flow-performance sensitivity among the high-fWHR hedge funds that they invest in.

[Insert Table 8 here]

3.6. Fund incentive alignment

Does incentive alignment ameliorate the effect of fWHR on fund performance? To the extent that high-fWHR managers are self-aware, greater incentive alignment should curb the suboptimal trading behavior of high-fWHR fund managers. However, funds with greater incentive alignment, e.g., those where the managers co-invest personal capital, tend also to have higher powered incentives, which may appeal to aggressive, high-fWHR managers. Insofar as these high-fWHR managers can autonomously increase their pay-performance

[22] We investigate fund flow response to CAPM alpha as Agarwal, Green, and Ren (2018) show that hedge fund flows are better explained by CAPM alphas than by alphas from more sophisticated models.

sensitivity, e.g., by co-investing personal capital, funds with greater incentive alignment will also tend to be managed by managers with higher fWHR. In the presence of this endogeneity effect, incentive alignment may not dampen the effect of fWHR on performance, especially if the negative relation between fWHR and performance is stronger within the sample of high-fWHR funds.

In this section, we investigate the effects of incentive alignment on the underperformance associated with fWHR by exploring two incentive alignment channels: (i) manager total delta, which is less impacted by endogeneity, and (ii) personal capital, which is more susceptible to endogeneity. Agarwal, Daniel, and Naik (2009) argue that funds with higher manager total deltas, i.e., those that are operating closer to their high-water marks, are more motivated and therefore tend to outperform. How close a fund is to its high-water mark is dependent on fund performance and the timing of capital inflows, and cannot be easily manipulated by the fund manager. Therefore, as an incentive alignment tool, manager total delta is less affected by endogeneity concerns.

To evaluate the effect of manager total delta on the relation between fWHR and performance, each year we sort the sample of hedge funds based on manager total delta at the end of the previous year. We classify funds in the top and bottom 30th percentiles based on manager total delta as high- and low-manager total delta funds, respectively. Next, we rerun our baseline performance regressions on these two groups of funds. The results reported in columns (1) to (4) of Table 9 indicate that incentive alignment ameliorates the impact of fWHR on performance when endogeneity effects are minimal. The coefficient estimates on $FWHR$ is negative and statistically significant at the 1% level for funds with low manager total deltas but is statistically indistinguishable from zero for funds with high manager total deltas.[23] In addition, when we estimate analogous regressions on both high- and low-manager total delta funds and include a dummy for high-manager total delta funds as well as the interaction of the dummy with $FWHR$, we find that the coefficient estimate

[23]We obtain qualitatively similar results with manager option deltas.

on the interaction variable is positive and statistically significant at the 5% level.

[Insert Table 9 here]

Personal capital, as an incentive alignment mechanism, is susceptible to the endogeneity concerns described above. High-fWHR fund managers may co-invest personal capital to aggressively increase their pay-performance sensitivity. Consistent with this view, we find in results reported in columns (5) to (8) of Table 9 that the relation between fund performance and fWHR is stronger for funds with personal capital than for funds without personal capital. For funds with personal capital, the coefficient estimates on $FWHR$ are negative and statistically significant at the 5% level. Conversely, for funds without personal capital, they are statistically unreliable. Therefore, in this case, incentive alignment fails to weaken the association between fWHR and fund performance. We find in unreported results that these findings can be traced to the fact that funds with personal capital tend also to have higher fWHR. Collectively, the findings suggest that incentive alignment attenuates the fWHR-performance relation, but only when fund managers cannot autonomously shape the incentive mechanism itself.

4. Alternative explanations

Sample selection may cloud inferences from our results. Our sample only includes fund managers whose images are available via an Internet search. If the availability of manager images is positively correlated with investment ability for low-fWHR managers but not for high-fWHR managers, this may explain why we find that for managers with available images, fWHR is negatively associated with performance. In general, the coefficients in Table 3 that supposedly explain the variation in fund performance could be contaminated by correlation between the residuals in those cross-sectional regressions and the unobserved factors that shape the availability of fund manager images. To address these issues, we employ the Heckman (1979) two-stage procedure to correct for possible sample selection bias. To apply this procedure, we first estimate a probit regression on the entire universe of hedge funds to determine the factors underlying selection. The inverse Mills ratio is then computed from this first stage probit and incorporated into the regressions on fund performance to correct for selection bias.

To implement the Heckman correction, a critical identifying assumption is that some variables explain selection but not performance. If there is no such exclusion restriction, the model is identified by only distributional assumptions about the residuals, which could lead to problems in estimating the model parameters. The exclusion restriction that we employ is the logarithm of firm AUM at inception. Managers of funds in firms with greater AUM at inception may attract greater media attention. Therefore, it is more likely that their facial images will be available via an Internet search. At the same time, it is unlikely that, controlling for other fund attributes such as fund size, inception firm AUM significantly explains future fund performance. To further ensure that inception firm AUM does not explain fund performance, we exclude fund returns reported within a year of firm inception.

Therefore, to correct for sample selection, we first estimate a probit regression on the probability that the manager facial image is available with the logarithm of firm inception AUM as the independent variable. In line with our intuition, the coefficient estimate on the logarithm of firm inception AUM in the selection equation, reported in column (3) of Table 10, is positive and statistically significant at the 1% level. In the Heckman model, the coefficient estimate on the inverse Mills ratio takes the sign of the correlation between the residuals in the regression that explain selection and hedge fund performance. In all the performance regressions, the coefficients on the inverse Mills ratio are negative, albeit statistically indistinguishable from zero. The sign suggests that managers whose images are available on the Internet deliver poorer performance. Regardless of the reasons for this, the estimates from the second stage regressions reported in columns (4) and (5) of Table 10 indicate that our findings are even stronger after controlling for sample selection.

[Insert Tables 10 and 11 here]

Marital status may drive our findings (Love, 2010; Roussanov and Savor, 2014). If high-fWHR men are more likely to marry and marriage hurts performance, then this may explain why we find that performance is negatively related to fWHR. To control for marital status, we first merge our data with marriage and divorce data that are publicly available for 13 states in the U.S.[24] We are able to obtain marital records for 147 out of the 478 fund managers that operate in the 13 states. Using those records, we construct an indicator variable for whether a manager is married or single. We assume that managers who operate in those states but do not have marital records are single. The results from the baseline performance regressions augmented with the marriage dummy are reported in Panel A of Table 11. They indicate that inferences remain unchanged after controlling for marital status.[25]

The results may also be driven by a firm effect. Capable firms may hire low-fWHR managers while less capable firms may hire high-fWHR managers. Therefore, our baseline results may be driven by differences in the quality of the firms that hire low- versus high-fWHR managers as opposed to differences in fund manager skill. To control for this, we include firm fixed effects in the baseline performance regressions. As shown in Panel B of Table 11, inferences remain unchanged after this adjustment.

Manager biological age may also drive our results. To account for manager biological age, we cull data on fund manager date of birth from Peoplewise (www.peoplewise.com), which are available for about 53.68% of the managers in our sample.[26] Next, we rerun the baseline regressions for this subsample after including an additional independent variable for

[24]The 13 states that publicly disclose marital records are Arizona, California, Colorado, Connecticut, Florida, Georgia, Kentucky, Nevada, North Carolina, Ohio, Pennsylvania, Texas, and Virginia. See Lu, Ray, and Teo (2016) for more information on the data.

[25]To address concerns that high-fWHR managers are more likely to get married and divorced, and that marital events distract fund managers from their investment duties (Lu, Ray, and Teo, 2016), we remove returns reported during the six-month period around each marriage and divorce from the sample of fund managers in the 13 states and redo the baseline regressions. We find that the baseline findings are virtually unchanged with this adjustment suggesting that limited attention does not drive our results.

[26]We find that high- and low-fWHR managers are on average 43.7 and 42.9 years old, respectively. The biological age difference is statistically indistinguishable from zero at the 10% level. While it is well established that testosterone decreases in men after age 40 (Feldman et al., 2002), our results do not necessarily imply that performance also improves with age since old age is associated with other changes including a potential loss of mental acuity (Peters, 2006).

manager age. The results reported in Panel C of Table 11 indicate that inferences remain unchanged with this adjustment.

Salivary testosterone is positively associated with sensation seeking albeit for young men between ages 18 to 23 years (Campbell et al., 2010). Therefore, insofar as fWHR is related to salivary testosterone, sensation seeking may be responsible for our findings. To control for sensation seeking, we cull information on new vehicles purchased by hedge fund managers from 2006 to 2012 from vin.place.[27] For the 1,086 funds in the sample with vehicle information, we construct a sports car indicator variable that takes a value of one if a manager in the fund purchased a sports car, and a value of zero otherwise. Brown et al. (2018) argue that sensation seekers are more likely to purchase sports cars than are nonsensation seekers. The coefficient estimates from the baseline performance regressions with this additional control variable are reported in Panel D of Table 11 and suggest that sensation seeking does not drive our findings. In untabulated results, we follow Grinblatt and Keloharju (2009) and control for sensation seeking by including an additional independent variable based on the number of speeding tickets incurred by each manager. We cull speeding ticket information by searching for court records on the PeopleFinders dataset using manager name, city, and state. The baseline performance regression results are again robust to including this additional control variable, further buttressing the view that sensation seeking does not drive our findings.

Managers who do not look the part may face greater difficulties raising capital. Popular stereotypes of successful investment managers may lead investors to believe that high-fWHR managers are more likely to succeed. Hence, our findings may be driven by the greater barriers to entry that low-fWHR fund managers face. To test, we compute the correlation between fund inception AUM and fund fWHR. We find that the correlation while positive is economically modest, i.e., at 0.0171, and statistically unreliable, casting doubt on the barriers to entry view. To further investigate, we sort hedge funds based on strategy flow

[27]See Brown et al. (2018) for more information on the data as well as on the sports car definition used.

during fund inception year. We find that the baseline results are even stronger for funds launched during years with above-median strategy flow, when barriers to entry are likely to be less pertinent. These results cast further doubt on the barriers to entry story.

5. Robustness tests

In this section, we conduct a medley of robustness tests to ascertain the strength of our empirical results.

5.1. Backfill bias

If hedge funds managed by high-fWHR managers are less likely to backfill their returns, this could explain why we find that they underperform. To address backfill bias concerns, we rerun the baseline performance regressions after dropping returns reported prior to fund listing. This necessitates that we limit the fund sample to TASS and HFR since only these databases provide data on fund listing date. The results reported in Panel E of Table 11 indicate that our findings are not driven by backfill bias.

5.2. Serial correlation in fund returns

Serial correlation in fund returns could arise from linear interpolation of prices for illiquid and infrequently traded securities or the use of smoothed broker dealer quotes. This could inflate some of the test statistics that we use to make inferences. To allay such concerns, we reestimate the baseline regressions after unsmoothing fund returns using the algorithm of Getmansky, Lo, and Makarov (2004). The results presented in Panel F of Table 11 indicate that our findings are robust to adjusting for serial correlation in fund returns.

5.3. Fund fees

Hedge fund returns are reported net of fees. If funds with high-fWHR managers charge higher fees than do funds with low-fWHR managers, this may explain the underperformance of the former. To derive pre-fee returns, it is important to match each capital outflow to the relevant capital inflow when calculating the high-water mark and the performance fee. In our pre-fee return calculation, we assume as per Appendix A of Agarwal, Daniel, and Naik (2009) that capital leaves the fund on a first-in, first-out basis. The results reported in Panel G of Table 11 indicate that our findings survive the imputation of fees.

5.4. Omitted risk factors

The presence of additional risk factors could cloud inferences from the fund alpha analysis. To ameliorate such concerns, we separately augment the Fung and Hsieh (2004) model with an emerging markets factor derived from the MSCI Emerging Markets Index return, with the out-of-the-money S&P 500 call and put option-based factors from the Agarwal and Naik (2004) model, and with the Pástor and Stambaugh (2003) liquidity factor. The results presented in Panels H, I, and J of Table 11 indicate that our baseline results are not driven by omitted risk factors. In findings that are available upon request, we find that the baseline results are robust to augmenting the Fung and Hsieh (2004) model with the volatility of aggregate volatility factor of Agarwal, Arisoy, and Naik (2017).

5.5. Fund termination

There are concerns that because funds that terminated their operations may have stopped reporting returns prematurely, the fund alphas are biased upward. To allay such concerns, we assume that, for the month after a fund liquidates, its return is –10%. As shown in Panel K of Table 11, the baseline results are robust to adjusting for fund termination in this way. We also experiment with more extreme termination returns of –20% and –30%, and obtain qualitatively similar results.

5.6. *Style-adjusted returns*

The Fung and Hsieh model may not adequately capture the risk exposures of the funds given the heterogeneity in investment styles. Therefore, we rerun the performance regressions with style-adjusted return and alpha. Fund style-adjusted return is simply the return of a fund minus the average return of the funds in the same investment style for that month. Fund style-adjusted alpha is defined analogously. The results reported in Panel L of Table 11 indicate that the baseline findings are robust to adjusting for investment style.

5.7. *Extreme fWHR*

The sort results in Table 2 suggest that our findings may be driven by funds with high fWHR. To test, each year we remove from the sample funds with fWHRs that are in the top 10th percentile and reestimate our baseline performance regressions. As shown in Panel M of Table 11, the coefficient estimates on $FWHR$ in the performance regressions shrink after omitting the extreme high fund fWHR observations from the sample. Nonetheless, they are still statistically significant at the 5% level.

5.8. *Fund performance manipulation*

If low-fWHR managers are more likely to inflate the returns that they report to commercial databases than are high-fWHR managers, this may explain why we find that high-fWHR managers underperform. To address such concerns, we rerun our baseline regressions with returns computed from Thomson Financial 13-F long-only filings that are reported to the SEC. Since these holdings are reported to the SEC, they are more costly to manipulate. The results reported in Panel N of Table 11 indicate that our findings are not driven by fund manager manipulation of reported fund returns.

5.9. *Manager race*

If fWHR varies systematically by manager race, our baseline findings may capture a race fixed effect instead. Since the overwhelming majority of our managers are Caucasians (2,709 out of the 2,744 managers), to address this concern, we reestimate the baseline regressions for this group of managers. The results reported in Panel O of Table 11 indicate that our findings are not driven by fund manager race.

5.10. *Alternative facial metrics*

Lefevre et al. (2013) report that face width-to-lower face height (henceforth fWLHR) is positively related while lower face height-to-whole face height (henceforth LH/WH) is negatively related to testosterone for men post potential mate exposure via a speed-dating event. Lower face height is the vertical distance between the highest point of the eyelids and the bottom of the chin. Whole face height is the vertical distance between the top of the forehead and the bottom of the chin. See their Table 2. To further test the testosterone view, we compute fWLHR and LH/WH for the managers in our sample and reestimate the baseline regressions with fWLHR or LH/WH in place of fWHR. The results reported in Panels P and Q of Table 11 suggest that our findings are qualitatively unchanged with these alternative biomarkers for testosterone.

5.11. *Female fund managers*

The literature finds that fWHR better predicts outcomes for men than for women (Carré and McCormick, 2008; Carré, McCormick, and Mondloch, 2009; Weston, Friday, and Liò, 2007). For example, Carré and McCormick (2008) find that fWHR predicts aggressiveness in males but not in females. Moreover, Lefevre et al. (2013) argue that because women have higher levels of oestrogen and growth hormone, which can also influence bone growth (Juul, 2001), facial morphology in men and women likely reflects different growth and endocrine mechanisms and is thus not easily comparable. Nonetheless, we compute fWHR for the 67 female managers in our hedge fund sample with valid photos. Next we rerun our baseline regressions with both male and female fund managers. The results reported in Panel R of Table 11 indicate that our findings are robust to including females in the sample. In unreported results that are available upon request, as a placebo test, we reestimate the baseline regressions with only female fund managers. Consistent with Carré and McCormick (2008), we find that fWHR is not related to performance among female hedge fund managers.

5.12. Manager roles

If the findings are driven by the impact of facial structure on investment management, our results should be stronger for managers who are primarily responsible for the investment activities at their funds. Moreover, it is important to square our findings with those of Wong, Ormiston, and Haselhuhn (2011) who show that higher fWHR maps to effective executive leadership. In that effort, we split the fund managers in our sample into Chief Investment Officers/Portfolio Managers, CEOs, and Others (Chief Risk Officers, Chief Operating Officers, etc). Manager role information is available for 2,401 of the 2,744 managers. Next, we redo the baseline regressions with the three groups of managers and report the findings in Table A3 of the Internet Appendix. Consistent with the view that facial structure has implications for investment management, the negative relation between fWHR and fund performance is more pronounced for Chief Investment Officers/Portfolio Managers. In keeping with the Wong, Ormiston, and Haselhuhn (2011) view, the erstwhile negative relation between fWHR and fund performance is no longer statistically reliable for fund management company CEOs.

6. Conclusion

Facial structure as summarized by fWHR positively correlates with a host of benefits. These benefits include alpha status in Capuchin monkeys, competitive success for professional Japanese baseball players, superior fighting skills among UFC fighters, effective executive leadership for firm CEOs, and stronger achievement drive in U.S. presidents. We show empirically that superior investment performance is not one of them.

We find that hedge funds operated by high-fWHR managers deliver substantially lower alphas, Sharpe ratios, and information ratios than do hedge funds operated by low-fWHR managers. In addition, masculine high-fWHR hedge fund managers take on greater operational risk which hurts investors. Funds operated by such managers are more likely to terminate early, report violations on their Form ADVs, and exhibit higher ω-scores – a univariate measure of operational risk. Moreover, high-fWHR managers are more likely to engage in suboptimal trading behavior such as purchasing lottery-like stocks and holding on to loser stocks. Interestingly, we find that fund investors are themselves affected by facial structure. High-fWHR fund investors operating FoFs underperform low-fWHR fund investors operating FoFs. Fund investors appear to invest in their own image. High-fWHR investors subscribe to hedge funds managed by high-fWHR managers while the low-fWHR investors gravitate toward hedge funds managed by low-fWHR managers. These results help us understand how high-fWHR fund managers can raise capital despite underperforming their competitors and exhibiting greater operational risk. Finally, we show that manager facial width can lead to heightened flow-performance sensitivity of hedge funds.

In the context of the ultra-competitive and male-dominated hedge fund industry, where masculine traits such as aggression, competitiveness, and drive are encouraged, expected, and even celebrated, our results on the underperformance of high-fWHR alpha males are enlightening. They indicate that, contrary to what popular stereotypes of successful investment managers imply, the masculine behaviors that map from fWHR can be inimical to investment management. These findings are relevant for investment fiduciaries who allocate capital to hedge funds as well as for hedge fund personnel who make hiring and staffing decisions. The results also underscore the importance of assessing manager facial structure when conducting operational due diligence in a fund management context.

References

Agarwal, V., Arisoy, Y.E., Naik, N.Y., 2017. Volatility of aggregate volatility and hedge fund returns. Journal of Financial Economics 125, 491–510.

Agarwal, V., Daniel, N., Naik, N. Y., 2009. Role of managerial incentives and discretion in hedge fund performance. Journal of Finance 64, 2221–2256.

Agarwal, V., Daniel, N., Naik, N. Y., 2011. Do hedge funds manage their reported returns? The Review of Financial Studies 24, 3281–3320.

Agarwal, V., Green, T.C., Ren, H., 2018. Alpha or beta in the eye of the beholder: what drives hedge fund flows? Journal of Financial Economics 127, 417–434.

Agarwal, V., Naik, N. Y., 2004. Risk and portfolio decisions involving hedge funds. The Review of Financial Studies 17, 63–98.

Agarwal, V., Ruenzi, S., Weigert, F., 2017. Tail risk in hedge funds: a unique view from portfolio holdings. Journal of Financial Economics 125, 610–636.

Aggarwal, R. K., Jorion, P., 2010. The performance of emerging hedge funds and managers. Journal of Financial Economics 96, 238–256.

Apicella, C.L., Dreber, B., Campbell, B., Gray, P.B., Hoffman, M., Little, A.C., 2008. Testosterone and financial risk preferences. Evolution and Human Behavior 29, 384–390.

Aragon, G. 2007. Share restrictions and asset pricing: evidence from the hedge fund industry. Journal of Financial Economics 83, 33–58.

Aragon, G., Nanda, V., 2017. Strategic delays and clustering in hedge fund reported returns. Journal of Financial and Quantitative Analysis 52, 1–35.

Aragon, G., Strahan, P., 2012. Hedge funds as liquidity providers: evidence from the Lehman bankruptcy. Journal of Financial Economics 103, 570–587.

Bai, J., Ma, L., Mullally, K., Solomon, D.H., 2019. What a difference a (birth) month makes:

the relative age effect and fund manager performance. Journal of Financial Economics, forthcoming.

Bali, T., Cakici, N., Whitelaw, R., 2011. Maxing out: stocks as lotteries and the cross-section of stock returns. Journal of Financial Economics 99, 427–446.

Barber, B., Odean, T., 2000. Trading is hazardous to your wealth: the common stock investment performance of individual investors. Journal of Finance 55, 773–806.

Barber, B., Odean, T., 2001. Boys will be boys: gender, overconfidence, and common stock investment. The Quarterly Journal of Economics 116, 261–292.

Berk, J., Green, R., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1269–1295.

Bhardwaj, G., Gorton, G., Rouwenhorst K.G., 2014. Fooling some of the people all of the time: the inefficient performance and persistence of commodity trading advisors. The Review of Financial Studies 27, 3099–3132.

Bird, B.M., Cid Jofré, V.S., Geniole, S.N., Welker, K.M., Zilioli, S., Maestripieri, D., Arnocky, S., Carré, J.M., 2016. Does the facial width-to-height ratio map onto variability in men?s testosterone concentrations? Evolution and Human Behavior 37, 392–398.

Bollen, N., Pool, V., 2012. Suspicious patterns in hedge fund returns and the risk of fraud. The Review of Financial Studies 25, 2673–2702.

Brown, S., Goetzmann, W., Liang, B., Schwarz, C., 2008. Mandatory disclosure and operational risk: evidence from hedge fund registration. Journal of Finance 63, 2785–2815.

Brown, S., Goetzmann, W., Liang, B., Schwarz, C., 2009. Estimating operational risk for hedge funds: The ω-score. Financial Analysts Journal 65, 43–53.

Brown, S., Goetzmann, W., Liang, B., Schwarz, C., 2012. Trust and delegation. Journal of Financial Economics 103, 221–234.

Brown, S., Lu, Y., Ray, S., Teo, M., 2018. Sensation seeking and hedge funds. Journal of Finance 73, 2871–2914.

Busse, J., Jiang, L., Tang, Y., 2019. Double-adjusted mutual fund performance. Unpublished working paper, Emory University.

Campbell, B.C., Dreber, A., Apicella, C.L., Eisenberg, D.T.A., Gray, P.B., Little, A.C., Garcia, J.R., Zamore, R.S., Lum, J.K., 2010. Testosterone exposure, dopaminergic reward, and sensation-seeking in young men. Physiology & Behavior 99, 451–456.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Carré, J.M., McCormick, C.M., 2008. In your face: facial metrics predict aggressive behavior in the laboratory and in varsity and professional hockey players. Proceedings of the Royal Society B: Biological Sciences 275, 2651–2656.

Carré, J.M., McCormick, C.M., Mondloch, C.J., 2009. Facial structure is a reliable cue of aggressive behavior. Psychological Science 20, 1194–1198.

Cesarini, D., Dawes, C.T., Johannesson, M., Lichtenstein, P., Wallace, B., 2009. Genetic variation in preferences for giving and risk taking. The Quarterly Journal of Economics 124, 809–842.

Cesarini, D., Johannesson, M., Lichtenstein, P., Sandewall, Ö., Wallace, B., 2010. Genetic variation in financial decision making. Journal of Finance 65, 1725–1754.

Chaudhuri, R., Ivković, Z., Pollet, J., Trzcinka, C., 2019. A tangled tale of training and talent: PhDs in institutional asset management. Unpublished working paper, Michigan State University.

Chevalier, J., Ellison, G., 1999. Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance. Journal of Finance 54, 875–899.

Coates, J.M., Gurnell, M., Rustichini, A., 2009. Second-to-fourth digit ratio predicts success among high-frequency financial traders. Proceedings of the National Academy of Sciences of the United States of America 106, 623–628.

Coates, J.M., Herbert, J., 2008. Endogenous steriods and financial risk taking on a London trading floor. Proceedings of the National Academy of Sciences of the United States of America 105, 6167–6172.

Cohen, R.B., Sandbulte, J.B., 2006. The Children's Investment Fund, 2005. Case 9-206-092. Harvard Business School, Boston, MA.

Cremers, M., Petajisto, A., 2009. How active is your fund manager? A new measure that predicts performance. The Review of Financial Studies 22, 3329–3365.

Cronqvist, H., Previtero, A., Siegel, S., White, R.E., 2016. The fetal origins hypothesis in finance: prenatal environment, the gender gap, and investor behavior. The Review of Financial Studies 29, 739–786.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035–1058.

Dimmock, S.G., Gerken, W.C., 2012. Predicting hedge fund fraud. Journal of Financial Economics 105, 153–173.

Feldman, H., Longcope, C., Derby, C., Johannes, C., Araujo, A., Coviello, A., Bremner, W., McKinlay, J., 2002. Age trends in the level of serum testosterone and other hormones in middle-aged men: longitudinal results from the Massachusetts male ageing study. Journal of Clinical Endocrinology & Metabolism 87, 589–598.

Fung, W., Hsieh, D., 2004. Hedge fund benchmarks: a risk based approach. Financial Analysts Journal 60, 65–80.

Fung, W., Hsieh, D., 2009. Measurement biases in hedge fund performance data: an update. Financial Analysts Journal 60, 36–38.

Geniole, S.N., Keyes, A.E., Carré, J.M., McCormick, C.M., 2014. Fearless dominance mediates the relationship between facial width-to-height ratio and willingness to cheat. Personality and Individual Differences 57, 59–64.

Getmansky, M., Lo, A., Makarov, I., 2004. An econometric model of serial correlation and illiquidity of hedge fund returns. Journal of Financial Economics 74, 529–610.

Grinblatt, M., Keloharju, M., 2009. Sensation seeking, overconfidence, and trading activity. Journal of Finance 65, 549–578.

Harlow, W.V., Brown, K.C., 1990. Understanding and assessing financial risk tolerance: a biological perspective. Financial Analysts Journal 46, 50–62.

Haselhuhn, M.P., Wong, E.M., 2012. Bad to the bone: facial structure predicts unethical behavior. Proceedings of the Royal Society B: Biological Sciences 279, 571–576.

He, X., Yin, H., Zeng, Y., Zhang, H., Zhao, H., 2019. Achievement drive and facial structure: evidence from financial analysts. Journal of Accounting Research, forthcoming.

Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161.

Hodges-Simeon, C.R., Sobraske, C.N.H., Samore, T., Gurven, M., Gaulin, S.J.C., 2016. Facial width-to-height ratio (fWHR) is not associated with adolescent testosterone levels. PLoS ONE 11, e0153083.

Jia, Y., van Lent, L., Zeng, Y., 2014. Masculinity, testosterone, and financial misreporting. Journal of Accounting Research 52, 1195–1246.

Juul, A., 2001. The effects of oestrogens on linear bone growth. Human Reproduction Update 7, 303–313.

Kamiya, S., Kim, Y.H., Park, S., 2019. The face of risk: CEO facial masculinity and firm risk. European Financial Management, forthcoming.

Kuhnen, C., Knutson, B., 2005. The neural basis of financial risk taking. Neuron 47, 763–770.

Kumar, A., 2009. Who gambles in the stock market? Journal of Finance 64, 1889–1933.

Lefevre, C.E., Lewis, G.J., Perrett, D.I., Penke, L., 2013. Telling facial metrics: facial width is associated with testosterone levels in men. Evolution and Human Behavior 34, 273–279.

Lefevre, C.E., Wilson, V.A.D., Morton, F.B., Brosnan, S.F., Paukner, A., Bates, T.C., 2014. Facial width-to-height ratio relates to alpha status and assertive personality in Capuchin monkeys. PLoS ONE 9, e93369.

Lewis, G.J., Lefevre, C.E., Bates, T.C., 2012. Facial width-to-height ratio predicts achievement drive in U.S. presidents. Personality and Individual Differences 52, 855–857.

Li, H., Zhang, X., Zhao, R., 2011. Investing in talents: manager characteristics and hedge fund performances. Journal of Financial and Quantitative Analysis 46, 59–32.

Liang, B., 2000. Hedge funds: the living and the dead. Journal of Financial and Quantitative Analysis 35, 309–326.

Lindberg, M.K., Vandenput, L., Movèrare, S.S., Vanderschueren, D., Boonen, S., Bouillon, R., Ohlsson, C., 2005. Androgens and the skeleton. Minerva Endocrinologica 30, 15–25.

Love, D., 2010. The effect of marital status and children on savings and portfolio choice. The Review of Financial Studies 23, 385–432.

Lu, Y., Ray, S., Teo, M., 2016. Limited attention, marital events, and hedge funds. Journal of Financial Economics 122, 607–624.

Mallaby, S., 2010. More Money Than God: Hedge Funds and the Making of a New Elite. Bloomsbury Publishing, London.

McDowell, L., 2010. Capital culture revisited: sex, testosterone, and the City. International Journal of Urban and Regional Research 34, 652–658.

Mehta, P.H., Beer, J., 2009. Neural mechanisms of the testosterone-aggression relation: the role of orbitofrontal cortex. Journal of Cognitive Neuroscience 22, 2357–2368.

Nadler, A., Jiao, P., Johnson, C.J., Alexander, V., Zak, P.J., 2018. The bull of Wall Street: experimental analysis of testosterone and asset pricing. Management Science 64, 4032–4051.

Nave, G., Nadler, A., Zava, D., Camerer, C., 2017. Single dose testosterone administration impairs cognitive reflection in men. Psychological Science 10, 1375–1386.

Nie, X., 2005. Cranial base in craniofacial development: development features, influence on facial growth, anomaly, and molecular basis. Acta Odontologica Scandinavica 63, 127–135.

Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance 53, 1775–1798.

Pástor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Perold, A., 2003. Maverick Capital. Case 9-204-013. Harvard Business School, Boston, MA.

Peters, R., 2006. Ageing and the brain. Postgraduate Medical Journal 82, 84–88.

Rasband, W.S., 2018. ImageJ. https://imagej.nih.gov/ij/

Reavis, R., Overman, W.H., 2001. Adult sex differences on a decision-making task previously shown to depend on the orbital prefrontal cortex. Behavioral Neuroscience 115, 196–206.

Riach, K., Cutcher, L., 2014. Built to last: aging, class and the masculine body in a UK hedge fund. Work, Employment and Society 28, 771–787.

Roussanov, N., Savor, P., 2014. Marriage and managers' attitudes to risk. Management Science 60, 2496–2508.

Siri, E.R., Tufano, P., 1998. Costly search and mutual fund flows. Journal of Finance 53, 1589–1622.

Sun, Z., Wang, A., Zheng, L., 2012. The road less traveled: strategy distinctiveness and hedge fund performance. The Review of Financial Studies 25, 96–143.

Teo, M., 2009. The geography of hedge funds. The Review of Financial Studies 22, 3531–3561.

Titman, S., Tiu, C., 2011. Do the best hedge funds hedge? The Review of Financial Studies 24, 123–168.

Tsujimura, H., Banissy, M.J., 2013. Human face structure correlates with professional baseball performance: Insights from professional Japanese baseball players. Biology Letters 9.

van Honk, J., Schutter, D.J., Hermans, E.J., Putnam, P., Tuiten, A., Koppeschaar, H., 2004. Testosterone shifts the balance between sensitivity for punishment and reward in healthy young women. Psychoneuroendocrinology 29, 937–943.

Verdonck, A., Gaethofs, M., Carels, C., de Zegher, F., 1999. Effect of low-dose testosterone treatment on craniofacial growth in boys with delayed puberty. European Journal of Orthodontics 21, 137–143.

Vigil, P., del Río, J.P., Carrera, B., Aranguiz, F.C., Rioseco, H., Cortés, M.E., 2016. Influence of sex steroid hormones on the adolescent brain and behavior: an update. The Linacre Quarterly 83, 308–329.

Welker K., Bird, B., Arnocky, S., 2016. Commentary: facial width-to-height ratio (fWHR) is not associated with adolescent testosterone levels. Frontiers in Psychology 7, 1745.

Weston, E.M., Friday, A.E., Liò, P., 2007. Biometric evidence that sexual selection has shaped the hominin face. PLoS ONE 2, e710.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48, 817–838.

Wong, E.M., Ormiston, M.E., Haselhuhn, M.P., 2011. A face only an investor would love: CEOs' facial structure predicts their firms' financial performance. Psychological Science 22, 1478–1483.

Zilioli, S., Sell, A., Stirrat, M., Jagore, J., Vickerman, W., 2015. Face of a fighter: bizygomatic width as a cue for formidability. Aggressive Behavior 41, 322–330.

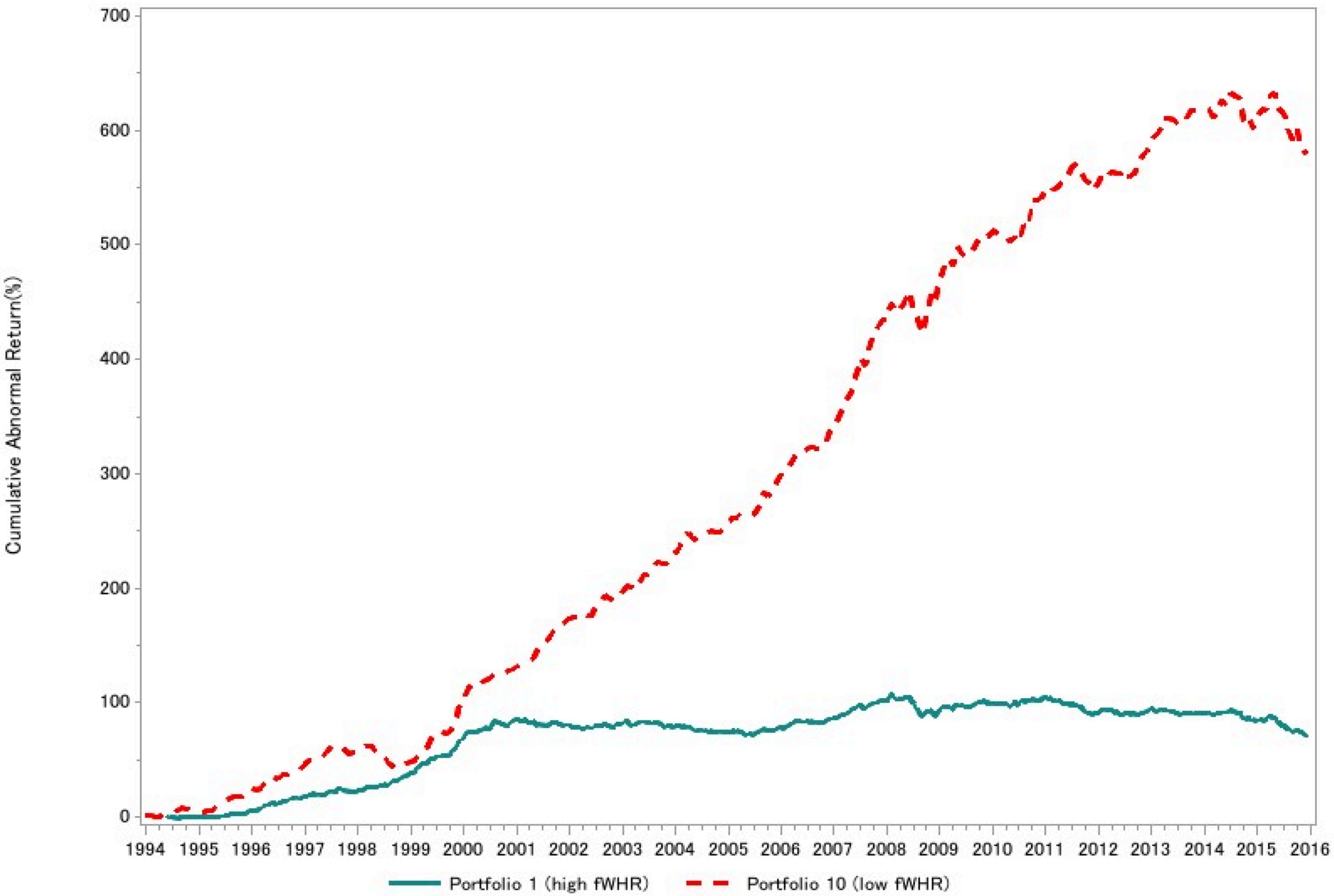

Fig 1. Cumulative abnormal returns of hedge funds managed by high-fWHR managers versus hedge funds managed by low-fWHR managers. Equal-weighted portfolios of hedge funds are constructed by sorting funds into ten portfolios based on the average manager fWHR for the fund. fWHR is facial width-to-height ratio. Only male managers are included in the sample. Portfolio 1 is the portfolio of funds with the highest fWHR. Portfolio 10 is the portfolio of funds with the lowest fWHR. Cumulative abnormal return is the difference between a portfolio's excess return and its factor loadings multiplied by the Fung and Hsieh (2004) risk factors. Factor loadings are estimated over the entire sample period. The sample period is from January 1994 to December 2015.

Table 1
Distribution of hedge fund manager fWHR and hedge fund fWHR by investment strategy

This table reports the distribution of hedge fund manager fWHR and hedge fund fWHR decomposed by investment strategy. The variable hedge fund manager fWHR is manager facial width-to-height ratio and proxies for fund manager testosterone. Following Carre, McCormick, and Mondloch (2009), it is computed as the distance between the two zygions (bizygomatic width) relative to the distance between the upper lip and the midpoint of the inner ends of the eyebrows (height of the upper face). Fund fWHR is the average fWHR of the managers managing a hedge fund. The strategy classification follows Agarwal, Daniel, and Naik (2009). Security Selection funds take long and short positions in undervalued and overvalued securities, respectively. Usually, they take positions in equity markets. Multi-process funds employ multiple strategies that take advantage of significant events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. Directional Trader funds bet on the direction of market prices of currencies, commodities, equities, and bonds in the futures and cash markets. Relative Value funds take positions on spread relations between prices of financial assets and aim to minimize market exposure. The sample period is from January 1994 to December 2015.

Investment strategy	Number of observations (1)	Mean (2)	Median (3)	Standard deviation (4)	Minimum (5)	25th Percentile (6)	75th Percentile (7)	Maximum (8)
Panel A: Manager fWHR								
Security Selection managers	1491	1.825	1.821	0.162	1.064	1.714	1.933	2.433
Multi-process managers	410	1.805	1.789	0.172	1.390	1.674	1.916	2.512
Directional Trader managers	479	1.831	1.836	0.159	1.367	1.712	1.938	2.333
Relative Value managers	364	1.826	1.815	0.175	1.282	1.708	1.922	2.558
All managers	2744	1.823	1.816	0.165	1.064	1.708	1.932	2.558
Panel B: Fund fWHR								
Security Selection funds	1714	1.826	1.818	0.147	1.064	1.730	1.914	2.417
Multi-process funds	465	1.815	1.806	0.158	1.390	1.697	1.911	2.512
Directional Trader funds	616	1.822	1.810	0.151	1.507	1.717	1.921	2.333
Relative Value funds	357	1.839	1.835	0.151	1.408	1.740	1.926	2.558
All funds	3152	1.825	1.816	0.150	1.064	1.727	1.917	2.558

Table 2
Portfolio sorts on hedge fund manager fWHR

Hedge funds are sorted into ten portfolios based on the average facial width-to-height ratio (fWHR) of the managers managing the funds. Only male managers are included in the sample. Hedge fund portfolio performance is estimated relative to the Fung and Hsieh (2004) factors. The Fung and Hsieh (2004) factors are S&P 500 return minus risk free rate (*SNPMRF*), Russell 2000 return minus S&P 500 return (*SCMLC*), change in the constant maturity yield of the U.S. 10-year Treasury bond appropriately adjusted for the duration (*BD10RET*), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), and commodities PTFS (*PTFSCOM*). The *t*-statistics derived from White (1980) standard errors are in parentheses. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

Hedge fund portfolio	Excess return (annualized) (1)	*t*-statistic of excess return (2)	Alpha (annualized) (3)	*t*-statistic of alpha (4)	*SNPMRF* (5)	*SCMLC* (6)	*BD10RET* (7)	*BAAMTSY* (8)	*PTFSBD* (9)	*PTFSFX* (10)	*PTFSCOM* (11)	Adj. R^2 (12)
Panel A: Full sample of hedge funds												
Portfolio 1 (high fWHR)	2.97*	2.11	0.41	0.38	0.27**	0.20**	-1.31**	-2.09**	0.00	0.01*	0.01	0.67
Portfolio 2	4.95**	3.07	1.69	1.67	0.31**	0.27**	-0.90*	-1.81**	-0.01	0.00	0.00	0.76
Portfolio 3	8.01**	5.14	4.86**	4.76	0.32**	0.21**	-1.06**	-1.28**	-0.02**	0.01*	0.00	0.74
Portfolio 4	7.98**	5.51	7.88**	7.29	0.32**	0.09**	-0.45	-1.86**	-0.00	0.01	-0.00	0.74
Portfolio 5	8.14**	4.64	5.68**	6.43	0.32**	0.19**	-0.49	-1.95**	-0.01	0.01	0.00	0.76
Portfolio 6	8.68**	3.73	6.31**	5.11	0.35**	0.16**	-0.32	-2.57**	-0.01	0.01	0.00	0.71
Portfolio 7	8.62**	5.79	6.30**	5.66	0.25**	0.19**	-0.77*	-2.38**	-0.00	0.01	-0.01	0.66
Portfolio 8	7.31**	4.33	4.87**	5.21	0.26**	0.17**	-0.35	-1.56**	-0.01	0.01	-0.00	0.67
Portfolio 9	7.67**	2.74	4.97**	3.88	0.33**	0.25**	-0.73	-2.55**	-0.01	0.01	0.00	0.69
Portfolio 10 (low fWHR)	9.11**	4.09	7.73**	4.59	0.33**	0.27**	-0.55	-2.27**	-0.02*	0.01	0.00	0.64
Spread (1-10)	-6.14*	-2.23	-5.83**	-3.36	-0.06	-0.07	-0.76	-0.18	0.02*	0.00	0.01	0.03
Panel B: Hedge funds with AUM >= US$20m												
Portfolio 1 (high fWHR)	2.06	1.62	0.26	0.34	0.23**	0.14**	-1.07**	-2.23**	-0.01*	0.02**	0.00	0.64
Portfolio 2	3.78*	2.26	1.27	1.26	0.30**	0.26**	-1.26**	-2.09**	-0.02*	0.01**	0.00	0.65
Portfolio 3	6.71**	4.37	4.18**	4.53	0.31**	0.19**	-1.33**	-1.44**	-0.02**	0.01	0.00	0.65
Portfolio 4	7.41**	5.22	5.42**	6.64	0.29**	0.18**	-0.29	-1.42**	-0.00	0.01	-0.00	0.68
Portfolio 5	7.45**	4.88	5.14**	6.56	0.29**	0.22**	-0.87**	-2.55**	-0.01*	0.00	0.01	0.74
Portfolio 6	6.88**	3.96	4.44**	4.23	0.30**	0.20**	-0.81*	-3.17**	-0.02**	0.01	0.00	0.65
Portfolio 7	5.23**	5.23	5.12**	6.32	0.22**	0.19**	-0.90**	-2.37**	-0.01**	0.01	0.00	0.65
Portfolio 8	4.95**	3.95	3.27**	3.82	0.23**	0.15**	-0.34	-0.93*	-0.01	0.00	0.00	0.54
Portfolio 9	7.07**	4.82	5.14**	5.11	0.22**	0.21**	-1.08**	-2.28**	-0.01	0.01	0.01	0.54
Portfolio 10 (low fWHR)	8.97**	4.31	5.90**	4.6	0.37**	0.25**	-0.90	-2.78**	-0.03**	0.01	-0.00	0.63
Spread (1-10)	-6.91**	-2.84	-5.64**	-3.78	-0.14**	-0.11	-0.17	-0.55	0.02	0.01	0.00	0.01

Table 3

Multivariate regressions on hedge fund performance

This table reports results from multivariate regressions on hedge fund performance. The dependent variables include hedge fund return (*RETURN*), alpha (*ALPHA*), Sharpe ratio (*SHARPE*), and information ratio (*INFORMATION*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. *SHARPE* is the average monthly fund excess returns divided by standard deviation of monthly fund returns. *INFORMATION* is the average monthly fund alpha divided by standard deviation of monthly fund residuals from the Fung and Hsieh (2004) model. *SHARPE* and *INFORMATION* are estimated over each nonoverlapping 24-month period after fund inception. The primary independent variable of interest is the average facial width-to-height ratio of the fund managers in the fund (*FWHR*). Only male managers are included in the sample. Another independent variable of interest is *FWHR* percentile rank (*FWHR_RANK*) which is computed every year and takes values from 0 to 1. The other independent variables include fund characteristics such as management fee (*MGTFEE* performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. The *t*-statistics are in parentheses. For the *RETURN* and *ALPHA* regressions, they are derived from robust standard errors that are clustered by fund and month. For the *SHARPE* and *INFORMATION* regressions, they are derived from robust standard errors that are clustered by fund. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variable							
	RETURN	*ALPHA*	*RETURN*	*ALPHA*	*SHARPE*	*INFORMATION*	*SHARPE*	*INFORMATION*
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FWHR	-0.529**	-0.375**			-0.367**	-0.725**		
	(-2.93)	(-3.35)			(-5.87)	(-4.01)		
FWHR_RANK			-0.246**	-0.193**			-0.212**	-0.366**
			(-3.02)	(-3.91)			(-6.54)	(-3.96)
MGTFEE	0.064	0.045	0.064	0.045	0.008	0.24	0.008	0.24
	(1.52)	(1.27)	(1.53)	(1.26)	(0.37)	(1.03)	(0.37)	(1.04)
PERFFEE	-0.004	0.006	-0.004	0.006	-0.001	0.013*	-0.001	0.013*
	(-0.87)	(1.52)	(-0.84)	(1.55)	(-0.34)	(1.97)	(-0.30)	(1.99)
HWM	0.110*	0.115*	0.107*	0.113*	0.002	-0.136	0.002	-0.138
	(2.21)	(2.31)	(2.12)	(2.28)	(0.06)	(-0.91)	(0.07)	(-0.93)
LOCKUP	0.079	0.030	0.078	0.029	0.026	-0.038	0.024	-0.041
	(1.94)	(0.83)	(1.93)	(0.80)	(0.97)	(-0.93)	(0.89)	(-1.01)
LEVERAGE	0.027	0.021	0.024	0.020	-0.046	0.008	-0.045	0.007
	(0.90)	(0.59)	(0.78)	(0.54)	(-1.48)	(0.16)	(-1.47)	(0.14)
AGE	-0.011**	-0.011**	-0.011**	-0.011**	-0.001	0.022	-0.001	0.022
	(-2.87)	(-3.51)	(-2.90)	(-3.53)	(-0.20)	(0.83)	(-0.24)	(0.83)
REDEMPTION	0.015**	0.004	0.015**	0.004	0.007	0.003	0.007	0.004
	(3.07)	(0.66)	(3.11)	(0.71)	(1.03)	(0.49)	(1.08)	(0.60)
log(*FUNDSIZE*)	-0.052**	-0.001	-0.051**	0.000	0.000	-0.048	0.001	-0.047
	(-3.58)	(-0.06)	(-3.53)	(0.01)	(-0.02)	(-1.06)	(0.13)	(-1.03)
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.027	0.015	0.027	0.015	0.046	0.016	0.047	0.016
N	150306	111893	150306	111893	5596	5600	5596	5600

Table 4
Multivariate regressions on hedge fund trading behavior metrics

This table reports results from multivariate regressions on hedge fund trading behavior metrics. The dependent variables include *TURNOVER*, *LOTTERY*, *DISPOSITION*, *NONSPRATIO*, and *ACTIVESHARE*. *TURNOVER* is the annualized turnover of a hedge fund manager's long-only stock portfolio. *LOTTERY* is the maximum daily stock return over the past one month averaged across stocks held by the fund as in Bali, Cakici, and Whitelaw (2011). *DISPOSITION* is percentage of gains realized (PGR) minus percentage of losses realized (PLR) as in Odean (1998). *NONSPRATIO* is the ratio of the number of non-S&P 500 index stocks bought in a quarter to the total number of new positions in the quarter. *ACTIVESHARE* is the Active Share (Cremers and Petajisto, 2009) relative to the S&P 500. The independent variable of interest is the average facial width-to-height ratio of the fund managers in the fund (*FWHR*). Only male managers are included in the sample. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. The *t*-statistics in parentheses are derived from robust standard errors that are clustered by fund. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variable				
	TURNOVER	*LOTTERY*	*DISPOSITION*	*NONSPRATIO*	*ACTIVESHARE*
Independent variable	(1)	(2)	(3)	(4)	(5)
FWHR	0.748	0.061**	0.236*	0.134**	0.059**
	(1.76)	(3.73)	(2.10)	(3.99)	(2.80)
MGTFEE	0.081	0.004	-0.033	-0.013	0.004
	(1.59)	(0.92)	(-1.04)	(-1.54)	(0.63)
PERFFEE	-0.017	0.001*	0.001	-0.000	-0.001
	(-1.17)	(2.34)	(0.29)	(-0.10)	(-1.44)
HWM	0.197	-0.000	0.022	-0.015	0.013
	(1.63)	(-0.05)	(0.55)	(-1.17)	(1.53)
LOCKUP	-0.144**	0.006	-0.057*	0.010	-0.015*
	(-3.48)	(1.05)	(-2.03)	(1.07)	(-2.00)
LEVERAGE	-0.064	0.007	0.006	0.013	0.001
	(-0.78)	(1.41)	(0.18)	(1.38)	(0.16)
AGE	-0.021*	0.000	0.004	-0.001	-0.006*
	(-1.96)	(0.09)	(0.37)	(-0.20)	(-2.13)
REDEMPTION	0.018	0.003*	0.005	0.000	-0.003*
	(1.80)	(2.45)	(0.86)	(0.30)	(-1.98)
log(*FUNDSIZE*)	0.021	0.002	-0.002	0.005*	-0.000
	(1.12)	(1.56)	(-0.28)	(2.34)	(-0.05)
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.035	0.082	0.080	0.050	0.054
N	1613	1521	513	1586	1640

Table 5

Multivariate regressions on hedge fund operational risk metrics

This table reports results from multivariate regressions on hedge fund operational risk metrics. The dependent variables include fund termination indicator (*TERMINATION*), Form ADV violation indicator (*VIOLATION*), and ω-Score (*OMEGA*). *TERMINATION* takes a value of one after a hedge fund stops reporting and states that it has liquidated, and takes a value of zero otherwise. *VIOLATION* takes a value of one when the hedge fund manager reports on his Form ADV that he has been associated with a regulatory, civil, or criminal violation, and takes a value of zero otherwise. *OMEGA* or fund ω-Score is an operational risk instrument derived from fund performance, volatility, age, size, fee structure, and other fund characteristics as per Brown et al. (2009). *OMEGA* is estimated over each non-overlapping 24-month period after fund inception. The primary independent variable of interest is the average facial width-to-height ratio of the fund managers in the fund (*FWHR*). Only male managers are included in the sample. The other independent variables include fund characteristics such as management fee (*MGTFEE* performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP* leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. The *t*-statistics in parentheses are derived from robust standard errors that are clustered by fund. The marginal effects are in brackets. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variable			
	TERMINATION		*VIOLATION*	*OMEGA*
	Logit	Cox	Logit	OLS
Independent variable	(1)	(2)	(3)	(4)
FWHR	0.694**	2.073**	1.612**	0.173*
	(3.93)	(4.11)	(3.63)	(2.21)
	[0.007]		[0.341]	
MGTFEE	-0.021	0.976	0.114	-0.008
	(-0.44)	(-0.52)	(0.88)	(-0.26)
PERFFEE	0.005	1.006	-0.020	-0.095**
	(1.11)	(1.27)	(-1.57)	(-22.29)
HWM	-0.133	0.885	0.220	-0.199**
	(-1.81)	(-1.73)	(1.11)	(-5.50)
LOCKUP	-0.060	0.943	-0.102	-1.572*
	(-1.12)	(-1.14)	(-0.71)	(-2.01)
LEVERAGE	0.109*	1.110*	-0.049	-0.108**
	(2.10)	(2.03)	(-0.35)	(-3.49)
AGE	0.031**	1.005	-0.052	-0.119**
	(6.10)	(0.27)	(-0.68)	(-26.50)
REDEMPTION	0.017	1.014	-0.009	-0.000
	(1.42)	(1.26)	(-0.36)	(-0.09)
log(*FUNDSIZE*)	-0.213**	0.805**	0.078*	0.003
	(-13.64)	(-12.15)	(2.18)	(0.53)
Strategy Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.084	0.064	0.020	0.756
N	119095	119207	1136	636

Table 6
Portfolio sorts on fund of hedge funds (FoF) manager fWHR

Funds of hedge funds (FoFs) are sorted into ten portfolios based on the average facial width-to-height ratio (fWHR) of the managers managing the FoFs. Only male managers are included in the sample. FoF portfolio performance is estimated relative to the Fung and Hsieh (2004) factors. The Fung and Hsieh (2004) factors are S&P 500 return minus risk free rate (*SNPMRF*), Russell 2000 return minus S&P 500 return (*SCMLC*), change in the constant maturity yield of the U.S. 10-year Treasury bond appropriately adjusted for the duration (*BD10RET*), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (*BAAMTSY*), bond PTFS (*PTFSBD*), currency PTFS (*PTFSFX*), and commodities PTFS (*PTFSCOM*). The t-statistics derived from White (1980) standard errors are in parentheses. The sample period is from January 1994 to December 2015. * Significant at the 5% level ** Significant at the 1% level.

	Excess return (annualized)	t-statistic of excess return	Alpha (annualized)	t-statistic of alpha	*SNPMRF*	*SCMLC*	*BD10RET*	*BAAMTSY*	*PTFSBD*	*PTFSFX*	*PTFSCOM*	Adj. R^2
Fund of hedge funds portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Portfolio 1 (high fWHR)	0.49	0.27	-1.07	-0.66	0.17**	0.05	-1.24*	-2.34**	-0.02*	0.02*	0.01	0.19
Portfolio 2	2.63*	2.25	1.24	1.47	0.17**	0.07**	-1.03**	-2.76**	-0.01	0.00	0.01	0.49
Portfolio 3	2.41*	2.00	0.98	1.01	0.14**	0.13**	-0.88*	-1.76**	-0.02**	0.01	0.00	0.37
Portfolio 4	4.15**	3.29	2.77**	2.84	0.18**	0.08**	-0.46	-2.22**	-0.01	0.01	0.00	0.42
Portfolio 5	3.50**	2.81	1.97**	2.28	0.20**	0.16**	-0.11	-1.41**	-0.01	0.00	0.00	0.53
Portfolio 6	5.33**	2.94	4.03*	2.32	0.13**	0.12**	-0.84	-1.41	-0.02	0.01	0.01	0.11
Portfolio 7	3.11**	2.42	1.54	1.51	0.16**	0.10**	-0.85*	-2.03**	-0.02**	0.01	0.01	0.39
Portfolio 8	2.79*	2.36	1.57	1.6	0.12**	0.12**	-0.93*	-2.16**	-0.02**	0.01*	0.01	0.33
Portfolio 9	3.66**	2.92	2.30*	2.24	0.16**	0.04	-1.48**	-2.48**	-0.01*	0.02**	0.01	0.35
Portfolio 10 (low fWHR)	4.87**	3.58	3.46**	2.97	0.17**	0.10**	-0.72	-1.65**	-0.01	0.00	0.01	0.28
Spread (1-10)	-4.39*	-1.97	-4.53*	-2.27	0.00	-0.05	-0.52	-0.69	-0.01	0.02**	0.00	-0.10

Table 7
Time series regressions on fund of hedge funds (FoF) portfolio excess returns

This table reports time-series regressions on fund of hedge funds (FoF) portfolio excess returns with hedge fund portfolio excess returns as independent variables. The high-fWHR FoF portfolio is the average excess return of all FoFs with fWHR in the top 30th percentile. The low-fWHR FoF portfolio is the average excess return of all FoFs with fWHR in the bottom 30th percentile. The medium-fWHR FoF portfolio is the average excess return of all other FoFs. Excess return is fund return in excess of the risk-free rate. The variable fWHR is facial width-to-height ratio. The high-, medium-, and low-fWHR hedge fund portfolios are defined analogously. Time-series regressions are estimated on the three FoF portfolios with the three hedge fund portfolios as independent variables. Time-series regressions are also estimated on the spreads between pairs of FoF portfolios with the same set of regressors. Spread 1 is the difference between the high- and low-fWHR FoF portfolios. Spread 2 is the difference between the high- and medium-fWHR FoF portfolios. Spread 3 is the difference between the low- and medium-fWHR FoF portfolios. The *t*-statistics derived from White (1980) standard errors are in parentheses. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Fund of hedge funds (FoF) portfolio					
	High-fWHR portfolio (HT)	Medium-fWHR portfolio (MT)	Low-fWHR portfolio (LT)	Spread 1 (HT-LT)	Spread 2 (HT-MT)	Spread 3 (LT-MT)
Hedge fund portfolio	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Without controlling for co-variation with the Fung and Hsieh (2004) factors						
High-fWHR portfolio (HT)	0.904**	-0.067	-0.951	1.855**	0.972*	-0.884
	(4.55)	(-0.12)	(-1.44)	(2.82)	(2.01)	(-1.10)
Medium-fWHR portfolio (MT)	0.463*	0.471	1.623*	-1.160	-0.008	1.152
	(2.13)	(0.85)	(2.27)	(-1.75)	(-0.02)	(1.26)
Low-fWHR portfolio (LT)	0.103	0.030	2.183**	-2.081**	0.073	2.153**
	(0.46)	(0.11)	(3.15)	(-3.19)	(0.20)	(2.66)
R^2	0.838	0.090	0.595	0.298	0.329	0.447
N	264	264	264	264	264	264
Panel B: Controlling for co-variation with the Fung and Hsieh (2004) factors						
High-fWHR portfolio (HT)	1.037**	0.102	-1.985**	3.022**	0.935	-2.087*
	(4.99)	(0.18)	(-2.78)	(4.23)	(1.94)	(-2.31)
Medium-fWHR portfolio (MT)	0.677**	0.224	1.139	-0.462	0.453	0.915
	(3.17)	(0.49)	(1.49)	(-0.66)	(0.98)	(0.97)
Low-fWHR portfolio (LT)	0.041	-0.004	2.666**	-2.625**	0.045	2.670**
	(0.19)	(-0.02)	(3.68)	(-3.85)	(0.13)	(3.25)
R^2	0.856	0.140	0.627	0.381	0.375	0.483
N	264	264	264	264	264	264

Table 8
Multivariate regressions on hedge fund flow

This table reports coefficient estimates from OLS multivariate regressions on hedge fund flow. The dependent variable is *FLOW* or the annual hedge fund flow in percentage. The independent variables of interest are *RANK*, *RANK_CAPM*, and *RANK_FH*. *RANK* is fund's fractional rank which represents its percentile performance, based on its past one-year return, relative to other funds in the same group in the same period and ranges from zero to one, as in Siri and Tufano (1998). *RANK_CAPM* is fund's fractional rank based on past one-year CAPM alpha. *RANK_FH* is fund's fractional rank based on its past one-year Fung and Hsieh (2004) alpha. One-year CAPM alpha is the monthly fund abnormal return relative to the CAPM averaged over the last year, where the betas are estimated over the last 24 months. One-year Fung and Hsieh (2004) alpha is computed analogously. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)). Controls are also included for strategy and year fixed effects. The regressions are estimated separately for two groups of hedge funds. The high-fWHR group comprises funds in the top 30th percentile based on fund fWHR. The low-fWHR group comprises funds in the bottom 30th percentile based on fund fWHR. The *t*-statistics derived from robust standard errors that are clustered by fund are in parentheses. The sample period is from January 1994 to December 2015. * Significant at the 5 level; ** Significant at the 1% level.

	Dependent variable = *FLOW*					
	high-fWHR hedge funds			low-fWHR hedge funds		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
RANK	0.385**			0.005		
	(3.78)			(0.05)		
RANK_CAPM		0.223**			0.151	
		(2.92)			(1.58)	
RANK_FH			0.223**			0.151
			(2.92)			(1.58)
MGTFEE	0.036	0.041	0.041	0.008	0.007	0.007
	(0.21)	(0.24)	(0.24)	(0.14)	(0.12)	(0.12)
PERFFEE	-0.003	-0.004	-0.004	0.009	0.009	0.009
	(-0.47)	(-0.65)	(-0.65)	(1.62)	(1.57)	(1.57)
HWM	0.051	0.055	0.055	-0.018	-0.017	-0.017
	(0.70)	(0.75)	(0.75)	(-0.17)	(-0.16)	(-0.16)
LOCKUP	-0.006	0.009	0.009	-0.119	-0.121	-0.121
	(-0.08)	(0.12)	(0.12)	(-1.65)	(-1.68)	(-1.68)
LEVERAGE	-0.074	-0.077	-0.077	0.107	0.107	0.107
	(-0.88)	(-0.92)	(-0.92)	(1.47)	(1.48)	(1.48)
AGE	0.023*	0.022*	0.022*	0.031**	0.031**	0.031**
	(2.36)	(2.26)	(2.26)	(3.50)	(3.59)	(3.59)
REDEMPTION	-0.017	-0.017	-0.017	0.002	0.002	0.002
	(-1.47)	(-1.47)	(-1.47)	(0.08)	(0.07)	(0.07)
log(FUNDSIZE)	0.044**	0.046**	0.046**	-0.003	-0.005	-0.005
	(2.99)	(3.18)	(3.18)	(-0.05)	(-0.07)	(-0.07)
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.038	0.033	0.033	0.051	0.052	0.052
N	1715	1715	1715	1651	1651	1651

Table 9
Multivariate regressions on hedge fund performance, subsample analysis

This table reports results from multivariate regressions on hedge fund performance. The dependent variables include hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The primary independent variable of interest is the average facial width-to-height ratio of the fund managers in the fund (*FWHR*). Only male managers are included in the sample. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. The *t*-statistics derived from robust standard errors that are clustered by fund and month are in parentheses. Manager total delta is as per defined in Appendix A of Agarwal, Daniel, and Naik (2009). Each year funds are sorted based on manager total deltas at the end of the previous year. Funds with high manager total deltas have manager total deltas in the top 30th percentile. Funds with low manager total deltas have manager total deltas in the bottom 30th percentile. The sample period is from January 1994 to December 2015. * Significant at the 5% level; **Significant at the 1% level.

	Funds with high manager total deltas		Funds with low manager total deltas		Funds with personal capital		Funds with no personal capital	
	RETURN	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FWHR	-0.382	-0.345	-0.894**	-0.673*	-0.321*	-0.504*	-0.458	-0.106
	(-0.95)	(-1.02)	(-2.62)	(-2.45)	(-2.02)	(-2.41)	(-1.44)	(-0.55)
MGTFEE	0.404**	0.222**	0.144	0.137	-0.074	-0.099	0.126	0.011
	(3.55)	(2.93)	(1.43)	(1.55)	(-0.79)	(-0.83)	(1.03)	(0.12)
PERFFEE	-0.001	0.017	-0.007	0.021**	-0.011	0.007	0.014	0.013
	(-0.05)	(1.96)	(-0.74)	(2.89)	(-0.69)	(0.48)	(1.37)	(1.82)
HWM	-0.156	-0.124	-0.162	-0.110	0.350**	0.154	0.184*	0.094
	(-1.02)	(-1.14)	(-1.59)	(-1.39)	(2.81)	(1.40)	(2.18)	(0.97)
LOCKUP	0.005	0.085	0.162	0.013	2.519	3.849	-0.077	2.092
	(0.04)	(1.02)	(1.67)	(0.23)	(0.89)	(1.82)	(-0.09)	(1.36)
LEVERAGE	0.141*	0.023	0.015	0.008	0.022	-0.071	0.015	0.082
	(2.37)	(0.37)	(0.17)	(0.09)	(0.17)	(-0.59)	(0.20)	(1.23)
AGE	-0.022*	-0.007	-0.012	0.001	-0.003	-0.004	-0.010	-0.003
	(-2.45)	(-0.71)	(-1.60)	(0.16)	(-0.30)	(-0.46)	(-1.04)	(-0.35)
REDEMPTION	0.006	0.006	0.022	-0.006	0.036	0.021	0.050*	0.032*
	(0.28)	(0.42)	(1.49)	(-0.67)	(1.70)	(0.91)	(2.26)	(2.25)
log(*FUNDSIZE*)	0.034	-0.014	0.062**	0.041*	-0.086*	-0.028	-0.026	0.027
	(0.93)	(-0.32)	(2.81)	(2.08)	(-2.09)	(-0.92)	(-0.62)	(1.69)
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.054	0.018	0.035	0.016	0.026	0.020	0.024	0.020
N	36510	36510	42684	42684	13623	10008	20844	14922

Table 10
Explaining hedge fund performance, controlling for selection bias

The Heckman (1979) selection model is used to control for selection bias in regressions on the cross-section of hedge fund performance. Two sets of regressions are estimated: one with monthly return (*RETURN*) as the dependent variable and another with monthly alpha (*ALPHA*) as the dependent variable. *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The primary independent variable of interest is the average facial width-to-height ratio of the fund managers in the fund (*FWHR*). Only male managers are included in the sample. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. Columns 1 and 2 report the regression results before correcting for selection bias. Column 3 reports the results from a probit selection equation, estimated using maximum likelihood, for the probability of a hedge fund being managed by a manager whose facial image is available on the internet. The exclusion restriction we use in the selection equation is the log of firm inception AUM (log(*INCEPTIONSIZE*)). Columns 4 and 5 report the regression results after correcting for selection bias. The t-statistics in parentheses are derived from robust standard errors that are clustered by fund and month. The z -statisti are in brackets. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

			Heckman model		
	OLS regression		Selection	Regression equation	
	RETURN	*ALPHA*	equation	*RETURN*	*ALPHA*
Independent variable	(1)	(2)	(3)	(4)	(5)
FWHR	-0.529**	-0.375**		-0.631**	-0.531**
	(-2.93)	(-3.35)		[-3.32]	[-4.20]
MGTFEE	0.064	0.045		0.081*	0.043
	(1.52)	(1.27)		[2.33]	[1.07]
PERFFEE	-0.004	0.006		-0.002	0.009
	(-0.87)	(1.52)		[-0.43]	[1.91]
HWM	0.110*	0.115*		0.041	0.017
	(2.21)	(2.31)		[0.74]	[0.28]
LOCKUP	0.079	0.03		0.059	-0.012
	(1.94)	(0.83)		[1.20]	[-0.29]
LEVERAGE	0.027	0.021		0.024	0.049
	(0.90)	(0.59)		[0.52]	[1.28]
AGE	-0.011**	-0.011**		0.022	0.034
	(-2.87)	(-3.51)		[0.85]	[0.73]
REDEMPTION	0.015**	0.004		0.004	0.007
	(3.07)	(0.66)		[0.55]	[0.72]
log(*FUNDSIZE*)	-0.052**	-0.001		-0.045**	-0.057*
	(-3.58)	(-0.06)		[-2.74]	[-2.54]
log(*INCEPTIONSIZE*)			0.021*		
			[2.52]		
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.027	0.015	0.012	0.002	0.003
N	150306	111893	10148	114880	106025

Table 11
Alternative explanations and robustness tests

This table reports robustness tests on the baseline multivariate regressions on hedge fund performance. The dependent variables include hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The primary independent variable of interest is the average facial width-to-height ratio of the fund managers in the fund (*FWHR*). Unless otherwise noted, only male managers are included in the sample. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. The coefficient estimates on these control variables are omitted for brevity. Panel A reports results after controlling for marital status via a marriage dummy. Panel B reports results after controlling for firm fixed effects. Panel C reports results after controlling for manager age. Panel D reports results after controlling for sensation seeking via manager sports car ownership. Panel E reports results adjusted for backfill bias by removing return observations before fund database listing date. Panel F reports results after unsmoothing returns using the Getmansky, Lo, and Makarov (2004) algorithm. Panel G reports results after adding back fees to form pre-fee returns. Panel H reports results after augmenting the Fung and Hsieh (2004) model with the MSCI Emerging Market Index excess return. Panel I reports results after augmenting the Fung and Hsieh (2004) model with the Pástor and Stambaugh (2003) liquidity factor. Panel J reports results after augmenting the Fung and Hsieh (2004) model with the Agarwal and Naik (2004) out-of-the-money call and put option factors. Panel K adjusts for fund termination by assuming that a fund delivers a -10% return for the month after it stops reporting. Panel L reports results for style-adjusted performance. Panel M reports results after excluding the top 10 percent of funds based on fWHR each January 1st. Panel N reports results from firm returns computed from Thomson Financial 13F stock holdings. Panel O reports results after limiting the sample to Caucasian managers. Panel P reports results with *FWLHR* in place of *FWHR*. *FWLHR* is facial width-to-lower height ratio and is positively related to testosterone (Lefevre et al., 2013). Panel Q reports results with *LH/WH* in place of *FWHR*. *LH/WH* is facial lower height-to-whole face height ratio and is negatively related to testosterone (Lefevre et al., 2013). Panel R reports results after including female managers in the sample. The *t* statistics in parentheses are derived from robust standard errors that are clustered by fund and month. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variable			Dependent variable	
	RETURN	*ALPHA*		*RETURN*	*ALPHA*
Independent variable	(1)	(2)	Independent variable	(3)	(4)
Panel A: Controlling for marital status			*Panel J: FH (2004) model augmented with Agarwal and Naik (2004) OTM call and put option factors*		
FWHR	-0.531**	-0.516**	*FWHR*	-0.529**	-0.341*
	(-2.96)	(-3.65)		(-2.97)	(-2.31)
Panel B: Controlling for firm fixed effects			*Panel K: Adjusted for termination returns*		
FWHR	-0.438*	-0.408**	*FWHR*	-0.508**	-0.503**
	(-2.48)	(-2.74)		(-2.85)	(-3.42)
Panel C: Controlling for manager age			*Panel L: Style-adjusted return and alpha*		
FWHR	-0.530**	-0.512**	*FWHR*	-0.210**	-0.566**
	(-3.02)	(-3.64)		(-7.36)	(-5.03)
Panel D: Controlling for sensation seeking			*Panel M: Exclude funds in the top ten percentile based on fWHR*		
FWHR	-0.774**	-0.847*	*FWHR*	-0.366*	-0.356*
	(-3.51)	(-2.15)		(-2.01)	(-2.30)
Panel E: Adjusted for backfill bias			*Panel N: Returns computed from 13-F long-only holdings*		
FWHR	-0.549**	-0.451*	*FWHR*	-0.783**	-0.427**
	(-2.84)	(-2.39)		(-4.78)	(-3.52)
Panel F: Adjusted for serial correlation			*Panel O: Caucasian only sample*		
FWHR	-0.286*	-0.322**	*FWHR*	-0.505**	-0.365**
	(-2.08)	(-2.68)		(-2.78)	(-3.22)
Panel G: Pre-fee returns			*Panel P: Facial width-to-lower height ratio (FWLHR)*		
FWHR	-0.590**	-0.393**	*FWLHR*	-0.283**	-0.267**
	(-2.63)	(-2.98)		(-3.29)	(-3.97)
Panel H: FH (2004) model augmented with emerging markets factor			*Panel Q: Facial lower height-to-whole face height ratio (LH/WH)*		
FWHR	-0.529**	-0.461**	*LH/WH*	1.836**	1.831*
	(-2.97)	(-2.73)		(2.59)	(2.12)
Panel I: FH (2004) model augmented with Pástor and Stambaugh (2003) liquidity factor			*Panel R: Including female fund managers*		
FWHR	-0.529**	-0.593**	*FWHR*	-0.502**	-0.361**
	(-2.97)	(-3.14)		(-2.92)	(-3.39)

Internet Appendix: Do Alpha Males Deliver Alpha? Facial Structure and Hedge Funds

Table A1

Multivariate regressions on hedge fund performance with trading behavior metrics as independent variables

This table reports results from multivariate regressions on hedge fund performance. The dependent variables include hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The independent variables of interest include *TURNOVER*, *LOTTERY*, *DISPOSITION*, *NONSPRATIO*, and *ACTIVESHARE*. *TURNOVER* is the annualized turnover of a hedge fund manager's long-only stock portfolio. *LOTTERY* is the maximum daily stock return over the past one month averaged across stocks held by the fund as in Bali, Cakici, and Whitelaw (2011). *DISPOSITION* is percentage of gains realized (PGR) minus percentage of losses realized (PLR) as in Odean (1998). *NONSPRATIO* is the ratio of the number of non-S&P 500 index stocks bought in a quarter to the total number of new positions in the quarter. *ACTIVESHARE* is Active Share (Cremers and Petajisto, 2009) relative to the S&P 500. These trading behavior metrics are computed in the prior quarter. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. The *t*-statistics in parentheses are derived from robust standard errors that are clustered by fund and month. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variable									
	RETURN	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TURNOVER	-0.131**	-0.098								
	(-2.70)	(-1.83)								
LOTTERY			-2.860*	-2.972**						
			(-2.06)	(-3.35)						
DISPOSITION					-1.680**	-1.880**				
					(-2.77)	(-3.30)				
NONSPRATIO							-0.058**	-0.033		
							(-3.42)	(-1.85)		
ACTIVESHARE									-0.106**	-0.067*
									(-4.07)	(-2.45)
MGTFEE	0.077	0.046	0.079*	0.047	0.079*	0.047	0.077	0.046	0.077	0.046
	(1.94)	(1.20)	(1.98)	(1.23)	(1.98)	(1.23)	(1.92)	(1.20)	(1.91)	(1.20)
PERFFEE	-0.003	0.003	-0.003	0.003	-0.003	0.002	-0.003	0.003	-0.003	0.003
	(-0.55)	(0.47)	(-0.60)	(0.43)	(-0.60)	(0.42)	(-0.56)	(0.46)	(-0.58)	(0.43)
HWM	0.052	0.067	0.053	0.068	0.053	0.068	0.054	0.067	0.056	0.070
	(0.94)	(1.09)	(0.95)	(1.11)	(0.96)	(1.11)	(0.97)	(1.09)	(1.01)	(1.13)
LOCKUP	0.103*	0.119	0.113*	0.128	0.112*	0.127	0.099*	0.119	0.103*	0.124
	(2.14)	(1.64)	(2.41)	(1.79)	(2.40)	(1.79)	(2.06)	(1.64)	(2.14)	(1.69)
LEVERAGE	0.032	0.050	0.034	0.052	0.034	0.052	0.030	0.051	0.032	0.052
	(1.11)	(0.92)	(1.17)	(0.95)	(1.18)	(0.96)	(1.05)	(0.93)	(1.09)	(0.95)
AGE	-0.021**	-0.010	-0.021**	-0.010	-0.021**	-0.010	-0.022**	-0.010	-0.021**	-0.009
	(-4.13)	(-1.62)	(-4.17)	(-1.63)	(-4.17)	(-1.63)	(-4.30)	(-1.63)	(-4.24)	(-1.58)
REDEMPTION	0.015*	0.007	0.016*	0.007	0.016*	0.007	0.015*	0.007	0.015*	0.006
	(2.38)	(0.99)	(2.45)	(1.08)	(2.46)	(1.08)	(2.38)	(0.99)	(2.33)	(0.95)
log(*FUNDSIZE*)	0.021	0.000	0.018	-0.002	0.018	-0.002	0.020	0.000	0.020	0.000
	(1.46)	(0.01)	(1.22)	(-0.15)	(1.22)	(-0.15)	(1.39)	(0.02)	(1.38)	(0.02)
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.026	0.006	0.025	0.006	0.025	0.006	0.026	0.006	0.026	0.006
N	166164	122392	166164	122392	166164	122392	166164	122392	166164	122392

Table A2
Multivariate regressions on hedge fund risk

This table reports results from multivariate regressions on hedge fund risk. The dependent variables include hedge fund risk (*RISK*), idiosyncratic risk (*IDIORISK*), systematic risk (*SYSTEMRISK*), and tail risk (*RISK*). *RISK* is the standard deviation of monthly hedge fund returns. *IDIORISK* is the standard deviation of monthly hedge fund residuals from the Fung and Hsieh (2004) seven-factor model. *SYSTEMRISK* is the square root of the difference between the variance of monthly hedge fund returns and that of monthly hedge fund residuals. *TAILRISK* is tail risk as defined in Agarwal, Ruenzi, and Weigert (2018). The risk measures are estimated over each nonoverlapping 24-month period after fund inception. The independent variable of interest is the average facial width-to-height ratio of the fund managers in the fund (*FWHR*). Only male managers are included in the sample. The other independent variables include fund characteristics such as management fee (*MGTFEE* performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. The *t*-statistics in parentheses are derived from robust standard errors that are clustered by fund. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variable			
	RISK	*IDIORISK*	*SYSTEMRISK*	*TAILRISK*
Independent variable	(1)	(2)	(3)	(4)
FWHR	-0.611	-0.739	0.128	-0.057
	(-1.61)	(-1.61)	(0.35)	(-0.36)
MGTFEE	0.348	0.363*	-0.015	0.054
	(1.79)	(2.06)	(-0.18)	(0.88)
PERFFEE	-0.023*	-0.005	-0.018*	-0.001
	(-2.16)	(-0.47)	(-2.27)	(-0.12)
HWM	0.080	-0.135	0.215	-0.307
	(0.49)	(-0.61)	(1.33)	(-1.09)
LOCKUP	0.233**	0.221**	0.012	0.431
	(2.66)	(2.68)	(0.14)	(1.00)
LEVERAGE	0.149	0.307*	-0.158	-0.001
	(0.89)	(2.31)	(-0.96)	(-0.01)
AGE	0.023*	0.014	0.009	-0.015
	(2.51)	(0.62)	(0.51)	(-1.33)
REDEMPTION	0.046*	0.034	0.012	0.000
	(2.30)	(1.34)	(0.47)	(0.01)
log(*FUNDSIZE*)	-0.288**	-0.224**	-0.064*	-0.057*
	(-6.87)	(-6.27)	(-2.32)	(-2.09)
Strategy Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.165	0.233	0.219	0.009
N	5814	5814	5814	5814

Table A3
Multivariate regressions on hedge fund performance for managers sorted by role within fund

This table reports results from multivariate regressions on hedge fund performance. The dependent variables include hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The primary independent variable of interest is the average facial width-to-height ratio of the fund managers in a specific role within the fund (*FWHR*). Only male managers are included in the sample. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as dummy variables for year and fund investment strategy. Hedge fund managers are sorted into three groups based on their roles within their funds: Chief Investment Officers and Portfolio Managers, who are not also Chief Executive Officers (CIO/PM), Chief Executive Officers (CEO), and all other managers, e.g., Chief Risk Officers, Chief Operating Officers, etc (OTHERS). The *t*-statistics, in parentheses, are derived from robust standard errors that are clustered by fund and month. The sample period is from January 1994 to December 2015. * Significant at the 5% level; ** Significant at the 1% level.

	Hedge Fund Manager Role							
	CIO/PM		CEO		OTHERS		ALL	
	RETURN	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FWHR	-0.747**	-0.702**	-0.068	0.324	-0.386	-0.380**	-0.473**	-0.419**
	(-3.51)	(-4.06)	(-0.22)	(1.07)	(-1.82)	(-2.77)	(-2.68)	(-2.88)
MGTFEE	0.139	0.060	-0.158*	-0.172	0.042	0.051	0.056	0.015
	(1.59)	(0.84)	(-1.98)	(-1.82)	(0.87)	(1.12)	(1.24)	(0.32)
PERFFEE	-0.022*	-0.006	0.002	0.010	0.008	0.018**	-0.000	0.006
	(-2.43)	(-0.83)	(0.36)	(1.40)	(1.85)	(3.69)	(-0.03)	(1.09)
HWM	0.219*	0.186	0.029	0.192*	0.076	0.072	0.036	0.030
	(2.02)	(1.84)	(0.29)	(1.97)	(1.44)	(1.30)	(0.67)	(0.45)
LOCKUP	0.009	-0.070	0.210**	0.129*	0.113*	0.032	0.114*	0.073
	(0.12)	(-1.46)	(4.42)	(2.01)	(2.39)	(0.68)	(2.57)	(1.12)
LEVERAGE	0.061	0.040	0.057	0.019	0.009	0.018	0.034	0.034
	(1.17)	(0.69)	(0.91)	(0.23)	(0.30)	(0.40)	(1.33)	(0.61)
AGE	-0.011*	-0.008	-0.005	-0.008	-0.012**	-0.013**	-0.021**	-0.010
	(-2.20)	(-1.69)	(-0.65)	(-0.91)	(-3.33)	(-3.12)	(-4.14)	(-1.52)
REDEMPTION	0.022	-0.012	0.015	-0.016	0.006	0.003	0.011	0.002
	(1.77)	(-0.80)	(0.59)	(-0.69)	(0.96)	(0.49)	(1.35)	(0.33)
log(*FUNDSIZE*)	-0.033	0.020	-0.062*	0.056	-0.051**	-0.007	0.016	0.013
	(-1.01)	(1.53)	(-2.52)	(1.75)	(-3.82)	(-0.54)	(1.15)	(0.88)
Strategy Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.027	0.017	0.037	0.028	0.027	0.017	0.026	0.007
N	40487	30215	16677	12747	76882	56777	134046	99737