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Do Alpha Males Deliver Alpha? Facial Width-to-Height Ratio and Hedge Funds

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Abstract

An abundance of evidence relates facial width-to-height ratio (fWHR) to masculine behaviors in males. We show that hedge funds operated by high-fWHR managers underperform those operated by low-fWHR managers, bear greater downside risk, are more susceptible to fire sales, and fail more often. High-fWHR managers compensate for their underperformance by marketing their funds more aggressively, thereby garnering higher flows and fee revenues. By exploiting major personal events that shape testosterone, namely marriage and fatherhood, we trace the biological mechanism underlying the relation between fWHR and investment performance to circulating testosterone. Our findings are robust and extend to equity mutual funds.

I. Introduction

Facial width-to-height ratio (fWHR) – the bizygomatic width divided by the distance between the brow and the lip – maps onto a subset of masculine behavioral traits in males and may relate to testosterone (Lefevre, Lewis, Perrett, and Penke (2013)). For example, fWHR has been linked to alpha status (Lefevre, Wilson, Morton, Brosnan, Paukner, and Bates (2014)), aggression (Carré and McCormick (2008), Carré, McCormick, and Mondloch (2009)), competitiveness (Tsujimura and Banissy (2013), Zilioli, Sell, Stirrat, Jagore, and Vickerman (2015)), effective executive leadership (Wong, Ormiston, and Haselhuhn (2011)), and achievement

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drive (Lewis, Lefevre, and Bates (2012), He et al. (2019)). Despite the preponderance of aggressive and competitive behaviors observed among traders (Mallaby (2010), McDowell (2010), and Riach and Cutcher (2014)) and the trillions of assets managed by investment managers, we know little about the implications of fWHR for delegated portfolio managers. In this study, we fill this void by exploring the relation between fWHR and investment performance for male hedge fund managers.[1]

The hedge fund industry provides a fertile ground for exploring the implications of facial width on investment management. As some of the most sophisticated investors in financial markets (Brunnermeier and Nagel (2004)), hedge funds collectively managed US$3.31 trillion of assets by the end of the third quarter of 2020 (https://www.hedgefundresearch.com/sites/default/files/articles/2020.Q3.HFR_GIR.pdf). The dynamic and relatively unconstrained strategies hedge funds employ, which often involve short sales, leverage, and derivatives may appeal to high-fWHR managers given their aggressive nature (Carré and McCormick (2008), Carré, McCormick, and Mondloch (2009)). 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, Keyes, Carré, and McCormick (2014)). Anecdotal evidence suggests that in the male-dominated hedge fund industry, attributes associated with fWHR, such as aggression, competitiveness, and physical prowess, are often synonymous with professional success (Mallaby (2010)).[2] Moreover, unlike mutual funds, hedge funds are typically managed by their founder-owners. Therefore, by focusing on hedge funds as opposed to mutual funds, we sidestep concerns related to endogenous matching between firms and managers.

Our analysis reveals substantial differences in expected returns on decile portfolios of hedge funds sorted by fund manager fWHR. Hedge funds operated by high-fWHR managers underperform those operated by low-fWHR managers by an economically significant 4.43% per year (t-stat = 5.12) after adjusting for co-variation with the Fung and Hsieh (2004) 7 factors. The inferior performance of high-fWHR managers is not confined to small funds and cannot be traced to fund share restrictions and illiquidity (Aragon (2007), Sadka (2010)), incentives

[1]We focus on male managers as fWHR better predicts aggressive behaviors for men than for women (Carré and McCormick (2008), Carré, McCormick, and Mondloch (2009)). According to Lefevre et al. (2013), since women have higher levels of estrogen and growth hormone, which can also influence bone growth (Juul (2001)), facial morphology in men and in women likely reflect different growth and endocrine mechanisms and are thus not easily comparable. Consistent with this view, we show that our results do not apply to female hedge fund managers. We note that the overwhelming majority of hedge fund managers are males.

[2]For example, Steve Cohen of SAC Capital and Point72 Asset Management has been described by ex-employees as a driven, aggressive, and ruthless trader that presides over a "testosterone-charged" trading floor. See "Inside SAC's shark tank," Alpha, Mar. 1, 2010. According to Mallaby ((2010), p. 111), "to thrive at Julian 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." The short-seller, Jim Chanos of Kynikos Associates, bench-presses 300 lbs. See "Jim Chanos on bench-pressing, short selling, and the importance of immigration," Square Mile, Oct. 12, 2017.

(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)), and backfill bias (Fung and Hsieh (2009), Bhardwaj, Gorton, and Rouwenhorst (2014)).

We show that the behavioral traits that map from facial width can shape trading behavior and lead to suboptimal decisions. High-fWHR fund managers trade more actively, 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 relate fWHR to aggression (Carré and McCormick (2008), Carré, McCormick, and Mondloch (2009)) and competitiveness (Tsujimura and Banissy (2013)).[3] In line with the findings of Odean (1998) and Bali, Cakici, and Whitelaw (2011), high-fWHR managers' preference for lottery-like stocks and reluctance to sell loser stocks in turn engenders underperformance.

Haselhuhn and Wong (2012) and Geniole et al. (2014) show that fWHR predicts unethical behavior among men. For hedge funds, unethical behavior can lead to greater operational risk (Brown, Goetzmann, Liang, and Schwarz (2008), (2009), (2012)). In keeping with this view, high-fWHR managers disclose more regulatory actions as well as civil and criminal violations on their Form ADVs. They are also more likely to terminate their funds, even after controlling for past performance. Moreover, hedge funds managed by high-fWHR managers exhibit higher ω-Scores, a univariate measure of operational risk (Brown et al. (2009)). Do high-fWHR managers also take on more investment risk? While high-fWHR funds do not deliver more volatile returns, their returns feature greater downside deviations, higher downside betas, steeper maximum losses, and sharper maximum drawdowns, suggesting that they bear more left tail risk.

Given their aggressive and competitive tendencies, high-fWHR managers may take on excessive liquidity risk relative to their share restrictions. The resultant asset-liability mismatch should precipitate asset fire sales and purchases (Coval and Stafford (2007)) when investors redeem from and subscribe to high-fWHR funds, respectively. We find precisely this result. Relative to low-fWHR funds, high-fWHR funds bear more liquidity risk but offer better redemption terms to their investors. Moreover, for high-fWHR funds, those that experience strong inflows subsequently outperform those that experience strong outflows by an annualized 5.88% (t-stat = 2.32) in the following month, after adjusting for co-variation with the Fung and Hsieh (2004) factors. For low-fWHR funds, the corresponding spread is only −0.20% per annum (t-stat = −0.08). Consistent with the fire sales and purchases view, the abnormal spread return from the flow sort with high-fWHR funds is substantially higher when the Pástor and Stambaugh (2003) liquidity measure is low and funding liquidity, as measured by the Treasury–Eurodollar spread and aggregate hedge fund flows, is tight.

Facial width has been associated with greater achievement drive among U.S. presidents (Lewis, Lefevre, and Bates (2012)) and Chinese sell-side analysts (He, Yin, Zeng, Zhang, and Zhao (2019)). For hedge funds, achievement drive translates into intensive capital raising. After controlling for the usual suspects,

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

we find that high-fWHR managers attract more unconditional flows. They do so by reporting to more commercial hedge fund databases, offering more duplicate share classes, and participating in more hedge fund conferences, thereby lowering investor search and entry costs. Consequently, high-fWHR managers operate larger funds and harvest greater fee revenues. These results help rationalize why such managers can survive despite underperforming their competitors.

Our results are consistent with the vector of behavioral traits that maps from fWHR. What is the underlying biological mechanism that links fWHR to such behavioral attributes? The circulating testosterone hypothesis postulates that fWHR relates positively to baseline and reactive testosterone levels in men. Consistent with this hypothesis, Lefevre et al. (2013) show that fWHR positively relates to saliva-assayed testosterone for men before and after mate exposure. This hypothesis is, however, still open to debate (Bird, Jofré, Geniole, Welker, Zilioli, Maestripieri, Arnocky, and Carré (2016)). A companion view, the pubertal testosterone hypothesis, posits that fWHR's association with behavioral traits is tied to testosterone exposure in puberty, rather than to baseline or reactive testosterone in adulthood (Weston, Friday, and Liò, (2007), Welker, Bird, and Arnocky (2016)). To investigate whether testosterone drives our findings, we reestimate our baseline regressions with 2 alternative biomarkers for testosterone in place of fWHR. We find that managers with larger values of face width-to-lower face height and smaller values of lower face height-to-whole face height, which Lefevre et al. (2013) show are linked to higher levels of salivary testosterone, also underperform. These results are most consonant with the circulating testosterone view.[4]

This study is not immune to endogeneity concerns. For example, we need to entertain the possibility that people may stereotype broad-faced men as aggressive and deceptive, which in turn could nurture the expected behavior in these men. Alternatively, facial width could positively relate to facial adiposity and, therefore, negatively related to manager self-discipline. To address such concerns and further investigate the testosterone view, we take advantage of two major personal events that lead to sharp declines in testosterone levels for men: marriage and fatherhood. Evidence from endocrinology suggests that marriage (Mazur and Michalek (1998), Holmboe, Priskorn, Jørgensen, Skakkebaek, Linneberg, Juul, and Andersson (2017)) and fatherhood (Berg and Wynne-Edwards (2001), Gettler, McDade, Feranil, and Kuzawa (2011)) suppress circulating testosterone levels in males. Under the circulating testosterone view, such events should disproportionately impact high-fWHR managers given their higher *reactive* levels of testosterone. Testosterone suppression should also be greater for high-fWHR men in light of their higher *baseline* levels of testosterone and the findings of Berg and Wynne-Edwards (2001) who show that men with higher basal testosterone are more likely to experience testosterone depletion post-birth. Consistent with this view, we find that marriage and fatherhood substantially attenuate the underperformance of high-fWHR managers relative to low-fWHR managers. In line with prior work showing that testosterone

[4]These results do not necessarily imply, given the lower circulating testosterone levels of females, that female hedge fund managers outperform male hedge fund managers. Females differ from males in other ways that could also affect performance. For instance, females tend to have higher levels of estrogen than do males and it is not clear how estrogen affects investment performance.

suppression is greater for newly partnered men and fathers with young children, our results are stronger for precisely such fund managers. The findings are not driven by marriage and fatherhood affecting the relative performance of high- versus low-fWHR managers for reasons, such as limited attention and performance persistence, that are unrelated to testosterone. These results bolster the circulating testosterone view and provide insights into the biological mechanism relating fWHR to fund manager behavior.

We carefully consider and rule out several alternative explanations, including sample selection, sensation seeking, biological age, manager race, barriers to entry, overconfidence, and endogenous matching between managers and hedge fund firms. To adjust for sample selection, we employ the Heckman (1979) 2-stage procedure with firm strategy flow at inception as the exclusion restriction and find that the negative relation between fWHR and fund performance is even stronger after adjusting for possible sample selection bias. Our choice of exclusion restriction follows Asker, Farre-Mensa, and Ljungqvist (2015) and is robust to alternative specifications. The results are robust to controlling for sensation seeking using speeding tickets (Grinblatt and Keloharju (2009)) and sports car ownership (Brown, Lu, Ray, and Teo (2018)). To address any endogenous matching concerns, we control for fund management company fixed effects. We also redo the baseline regressions on the first funds of hedge fund firms, as firm founders are more likely to run such funds. None of our inferences change with these adjustments.

To test whether our findings extend beyond hedge funds, we redo the performance sorts and regressions on actively managed U.S. equity mutual funds. We find that mutual funds in the top fWHR decile underperform mutual funds in the bottom fWHR decile by a substantive 8.80% per annum (t-stat = 20.89) after adjusting for co-variation with the Carhart (1997) 4 factors. Inferences remain unchanged when we account for other fund characteristics that could explain mutual fund performance, analyze style-adjusted mutual fund performance, study pre-fee mutual fund returns, or evaluate mutual fund performance relative to the Fama and French (2016) 5-factor model. The greater underperformance of high- versus low-fWHR mutual funds relative to hedge funds is consistent with the self-selection biases inherent in hedge fund data (which are absent in mutual fund data) that could limit the number of return observations associated with extreme-fWHR hedge funds.

The findings deepen our understanding of fund manager skills. The results reveal that, just like motivated (Agarwal, Daniel, and Naik (2009)), emerging (Aggarwal and Jorion (2010)), low R^2 (Titman and Tiu (2011)), talented (Li, Zhang, and Zhao (2011)), and distinctive (Sun, Wang, and Zheng (2012)) hedge funds, those operated by managers with lower fWHR also outperform. This study also complements research in delegated portfolio management that relate to manager college selectivity (Chevalier and Ellison (1999)), confidence (Bai, Ma, Mullally, and Solomon (2019)) and Ph.D. training (Chaudhuri, Ivković, Pollet, and Trzcinka (2020)) to investment performance. Unlike the aforementioned studies, we uncover a biological component of managerial skill.

This article builds on an emerging literature that examines the association between fWHR and financial outcomes. It finds that 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)). We enrich this literature by analyzing the implications of fWHR for delegated portfolio managers and in the process provide insights into important issues such as behavioral biases, operational risk, downside risk, asset-liability mismatch, and marketing intensity. Our identification strategy addresses the shortcoming of this stream of research whereby the relation between fWHR and testosterone is often assumed but not assessed. In a related work, He et al. (2019) find that Chinese sell-side analysts with higher fWHRs issue more accurate earnings forecasts and ascribe their results to achievement drive. Our findings suggest that achievement drive may not be the dominant trait encapsulated by fWHR at least in the context of asset management. While high-fWHR fund managers raise more capital, which is consistent with greater achievement drive, they are also more susceptible to behavioral biases and bear greater downside risks. Consequently, they earn lower investment returns and alphas.

This study also resonates with work on testosterone and individual investor trading behavior. Research has shown in experimental settings that high-testosterone men overbid for assets (Nadler, Jiao, Johnson, Alexander, and Zak (2018)) and take on more risk (Apicella, Dreber, Campbell, Gray, Hoffman, and Little (2008)). In addition, Cronqvist, Previtero, Siegel, and White (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. 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 visuo-motor scanning abilities and sharp physical reflexes) may not be relevant for the more analytical forms of trading commonly employed by money managers.[5] Moreover, they do not control for risk. Our results suggest that testosterone is less beneficial for delegated portfolio managers. The findings dovetail with laboratory studies that show that testosterone can lead individuals to make irrational risk-reward tradeoffs (Reavis and Overman (2001), van Honk, Schutter, Hermans, Putnam, Tuiten, and Koppeschaar (2004), and Nave, Nadler, Zava, and Camerer (2017)).

The remainder of this article is structured as follows: Section II reviews the evidence relating fWHR to behavioral traits and testosterone in males and describes the data. Section III reports the empirical results. Section IV presents robustness tests while Section V investigates equity mutual funds. Section VI concludes.

[5]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 (2006)).

II. Data and Methodology

A. Testosterone, Behavior, and fWHR

Research has shown that fWHR relates to aggression, physical prowess, achievement drive, risk-taking, and deception in males. Carré and McCormick (2008) find that among both varsity and professional male hockey players, fWHR positively relates to aggressive behavior as measured by the number of penalty minutes per game incurred over a season. In a meta-analysis, Haselhuhn, Ormiston, and Wong (2015) demonstrate a robust positive link between fWHR and aggression in men. With respect to physical prowess, fWHR is associated with home run performance among professional Japanese baseball players (Tsujimura and Banissy (2013)) and fighting ability among professional mixed martial artists (Zilioli et al. (2015)). Moreover, fWHR is consonant with greater achievement drive for U.S. presidents (Lewis, Lefevre, and Bates (2012)) and for Chinese sell-side analysts (He et al. (2019)). It also predicts risk-taking behavior, albeit only for low-status men (Welker, Goetz, and Carré (2015)). However, Haselhuhn and Wong (2012) find that wide-faced men are also more likely to deceive their counterparts in a negotiation, and cheat to increase financial gain.

Testosterone has been proposed as the biological construct that relates fWHR to such behaviors in males. The exact mechanism by which testosterone relates to fWHR is still open to debate. The pubertal testosterone hypothesis posits that testosterone is responsible for the development of both facial bone structure and neural circuitry during puberty for males (Weston, Friday, and Liò (2007)), and it is the change in neural circuitry during adolescence that drives behavior in adulthood. Consistent with this view, Verdonck, Gaethofs, Carels, and de Zegher (1999) find that low doses of testosterone accelerate craniofacial growth among boys with delayed puberty. Lindberg, Vandenput, Movèrare Skrtic, Vanderschueren, Boonen, Bouillon, and Ohlsson (2005) and Clarke and Khosla (2009) document the relation between testosterone and bone growth. Morris, Jordan, and Breedlove (2004) show that testosterone masculinizes the developing nervous system, thereby promoting male behaviors. Similarly, Sisk, Schulz, and Zehr (2003) find that testosterone-dependent organization of neural circuits underlying male social behavior occurs during puberty. While Hodges-Simeon, Sobraske, Samore, Gurven, and Gaulin (2016) show that fWHR does not relate to testosterone for a sample of 75 adolescent Tsimane males, they do not control for age and adopt a liberal criterion for adolescence (i.e., ages 8–23 years). After controlling for age and limiting the Tsimane sample to adolescent males between 12 and 16 years old, Welker, Bird, and Arnocky (2016) document a strong and positive relation between fWHR and pubertal testosterone.

A companion view, the circulating testosterone hypothesis, postulates that fWHR relates to baseline and reactive testosterone levels in adulthood, which in turn shapes behavior. In line with this view, Lefevre et al. (2013) find that fWHR is positively associated with salivary testosterone in males both before and after a speed dating event. Moreover, testosterone relates to financial risk-taking (Apicella et al. (2008)), aggression (Batrinos (2012)), social dominance (Mehta, Jones, and Josephs (2008)), and egocentrism (Wright, Bahrami, Johnson, Di Malta, Rees, Frith, and Dolan (2012)), attributes that are also predicted by fWHR. Several studies show that circulating testosterone modulates social behavior through the amygdala, the part of the brain that is primarily involved in processing emotions (including fear, anxiety, and aggression). For instance, Radke, Volman, Mehta, van Son, Enter, Sanfrey, Toni, de Bruijn, and Roelofs (2015) show using functional magnetic-resonance imaging that testosterone administration increases amygdala response to social threat approach. Bos, Terburg, and van Honk (2010) argue that the amygdala responds to testosterone by reducing communication with the orbito-frontal cortex and activates the brainstem defense circuit, which leads to aggressive behavior in the face of a social threat. In a challenge to the circulating testosterone view, Bird et al. (2016) find no significant positive relation between fWHR and baseline testosterone or competition-induced testosterone reactivity in their meta-analysis. However, unlike Lefevre et al. (2013), Bird et al. (2016) are not able to control for age and body mass index, which can also affect testosterone (Feldman, Longcope, Derby, Johannes, Araujo, Coviello, Bremner, and McKinlay (2002), Diaz-Arjonilla, Schwarcz, Swerdloff, and Wang (2009)). Moreover, Bird et al. (2016) focus on video game competitions, which unlike speed dating events do not feature mate exposure and where the payoffs may not be large enough to elicit a significant testosterone reaction. Jia, van Lent, and Zeng (2014) provide an excellent review of literature relating fWHR to behavior and testosterone.

B. Hedge Fund and fWHR Data

We evaluate the relation between manager fWHR and hedge fund performance using monthly net-of-fee returns and assets under management (AUM) data of live and dead hedge funds reported in the Lipper TASS, Morningstar, Hedge Fund Research (HFR), and BarclayHedge data sets from Jan. 1994 to Dec. 2015. We focus on data from Jan. 1994 onward as the hedge fund data sets contain survivorship bias prior to Jan. 1994.

In our fund universe, we have a total of 38,084 hedge funds, of which 14,869 are live funds and 23,215 are dead funds. 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 22,071 hedge funds, of which 8,135 are live funds and 13,936 are dead funds. While 5,564 funds appear in multiple databases, many funds belong to only one database. Specifically, there are 5,635, 2,653, 4,383, and 3,836 funds unique to the Lipper TASS, Morningstar, HFR, and BarclayHedge databases, respectively, highlighting the advantage of obtaining data from multiple sources.

For each manager in the combined database, we use manager name and fund management company name to perform a Google image search for the manager's facial picture or pictures.[6] If we find multiple pictures 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)

[6]We obtain manager photos from investment management company websites, manager LinkedIn profiles, investment conference web pages, high society websites, news articles, and social media. On several occasions, we are able to find manager photos even when the manager has moved to another firm or has shut down his fund by searching for his current place of employment listed on his LinkedIn or Bloomberg profile.

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 2 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).[7] As discussed, we focus on male managers in our analysis. We do so by searching for the facial images of all managers and then excluding female managers from the sample by using manager name and facial image to determine gender. To address reproducibility concerns, we will redo our analysis with fWHR computed via a Python program as a robustness test.

Since measurement error can creep into the computation of fWHR if the manager is not fully forward facing or has significant facial adiposity around the cheek area, we exclude managers from the sample who are not fully forward facing in their photographs or who are in the top 10th percentile based on a subjective assessment of their facial adiposity.[8] In total, we obtain valid photos and compute fWHRs for 2,446 male fund managers. These managers operate 2,629 hedge funds and belong to 1,484 fund management companies. In this study, we use fund fWHR, defined as the average fWHR of the managers operating a hedge fund, as a proxy of the level of manager fWHR associated with a hedge fund.[9]

Following Agarwal, Daniel, and Naik (2009), we classify funds into 4 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.

Table 1 reports the distribution of fund manager fWHR and fund fWHR by investment strategy. The average manager fWHR is 1.818 with a standard deviation of 0.164. Similarly, the average fund fWHR is 1.824 with a standard deviation of 0.160. 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 in their Table 1 an average fWHR of 1.860 for their sample of 37 male undergraduates.[10] We also note that the hedge fund managers in

[7]See Figure 1 in Carré and McCormick (2008). Some researchers, such as Lefevre et al. (2013) and 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.

[8]Inferences remain unchanged when we include managers who are not fully forward facing or have significant facial adiposity in the sample. Measurements of fWHR could also be inflated for managers who smile broadly in their photos. Our findings remain qualitatively unchanged when we remove such managers from the sample. See Panel A in Supplementary Material Table S1.

[9]Our baseline results are robust when we analyze only hedge funds with one manager. In those cases, fund fWHR equals manager fWHR. See Panel B in Supplementary Material Table S1.

[10]The finding that the average fWHR of our sample of male hedge fund managers is similar to that from a sample of male undergraduates is not at odds with the finding of Sapienza, Zingales, and Maestripieri (2009) that salivary testosterone is positively correlated with the probability of entering

TABLE 1

Distribution of Hedge Fund Manager fWHR and Hedge Fund fWHR by Investment Strategy

Table 1 reports the distribution of hedge fund manager fWHR and hedge fund fWHR decomposed by investment strategy. Manager fWHR is manager facial width-to-height ratio. Following Carre, McCormick, and Mondloch (2009), it is computed as the distance between the 2 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 operating 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 Jan. 1994 to Dec. 2015.

Investment Strategy	No. of Obs.	Mean	Median	Std. Dev.	Minimum	25th Percentile	75th Percentile	Maximum
	1	2	3	4	5	6	7	8
Panel A. Manager fWHR								
Security selection managers	1,320	1.820	1.818	0.162	1.064	1.711	1.920	2.586
Multi-process managers	328	1.805	1.785	0.168	1.182	1.670	1.914	2.239
Directional trader managers	427	1.827	1.824	0.160	1.367	1.712	1.938	2.304
Relative value managers	371	1.811	1.811	0.170	1.282	1.697	1.919	2.558
All managers	2,446	1.818	1.815	0.164	1.064	1.704	1.923	2.586
Panel B. Fund fWHR								
Security selection funds	1,438	1.823	1.827	0.158	1.064	1.716	1.920	2.586
Multi-process funds	335	1.811	1.800	0.170	1.182	1.674	1.918	2.239
Directional trader funds	482	1.835	1.829	0.153	1.461	1.731	1.938	2.304
Relative value funds	374	1.830	1.833	0.166	1.408	1.714	1.932	2.558
All funds	2,629	1.824	1.825	0.160	1.064	1.714	1.924	2.586

our sample have lower fWHRs than do public company CEOs. For example, Jia, van Lent, and Zeng (2014) and Kamiya, Kim, and Park (2019) report average CEO fWHRs of 2.013 and 2.014, respectively. This provides prima facie evidence that a higher fWHR may be less beneficial for fund managers than it is for firm CEOs.

Figure 1 depicts the composite facial image from a random sample of 10 managers with fWHR in the bottom 10th percentile and that from a random sample of 10 managers with fWHR in the top 10th percentile. It illustrates the variation in fWHR within the hedge fund manager sample while preserving manager anonymity.

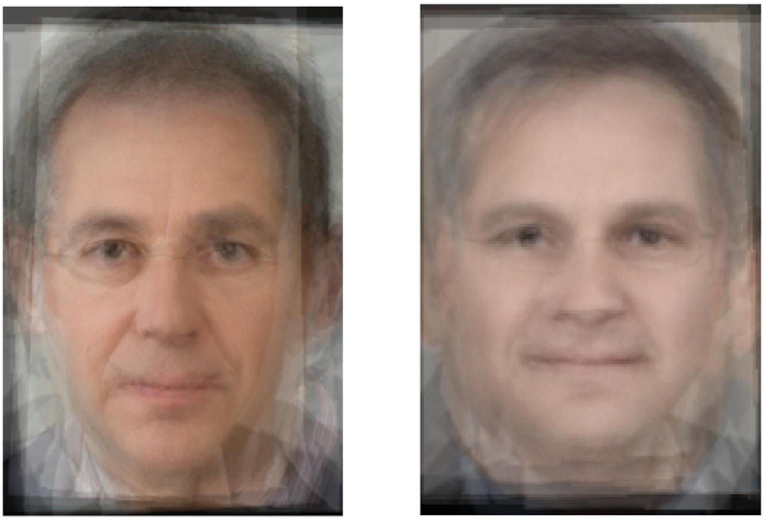
Throughout this article, we model the risk of hedge funds using the Fung and Hsieh (2004) 7-factor model. The Fung and Hsieh factors are the excess return on the S&P 500 index (SNPMRF); a small minus big factor (SCMLC) constructed as the difference between the Russell 2000 and S&P 500 stock indexes; the change in the 10-year Treasury constant maturity yield, appropriately adjusted for duration (BD10RET); the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration (BAAMTSY);

the finance industry, since their results apply to a mixed sample of males and females, and become statistically insignificant once they control for gender. See columns I and II in their Table 4.

FIGURE 1

Composite Facial Images

Figure 1 shows composite facial images of low-fWHR (left) and high-fWHR (right) hedge fund managers. fWHR is facial width-to-height ratio. Following Carre, McCormick, and Mondloch (2009), it is computed as the distance between the 2 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). Only male managers are included in the sample. The facial image on the left is the average of a random sample of 10 hedge fund managers with fWHR in the bottom 10th percentile. The facial image on the right is the average of a random sample of 10 hedge fund managers with fWHR in the top 10th percentile. The sample period is from Jan. 1994 to Dec. 2015.



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.[11] Fung and Hsieh show that these 7 factors have considerable explanatory power on aggregate hedge fund returns.

One concern is that the characteristics and performance of the funds with manager photos may differ significantly from those of funds without manager photos. To address such concerns, we compute the differences in fees, redemption period, lockup, age, size, leverage indicator, high-water mark indicator, monthly flow, monthly return, and monthly alpha between funds with and without manager photos. Monthly alpha is Fung and Hsieh (2004) abnormal return where factor loadings are estimated over the last 24 months. Supplementary Material Table S2 reveals that the differences in monthly return and monthly alpha between the 2 fund subsamples are economically modest at −5 and 4 basis points, respectively. Moreover, none of the differences in fund characteristics and performance are statistically distinguishable from 0 at the 5% level. Therefore, we cannot reject the null hypothesis that the sample of funds with valid manager photos is representative of the broader sample.

[11]David Hsieh kindly supplied these risk factors. The trend-following factors can be downloaded from http://faculty.fuqua.duke.edu/%7Edah7/DataLibrary/TF-Fac.xls.

III. Empirical Results

A. Fund Investment Performance

To begin, we test for differences in risk-adjusted performance of funds sorted by fund fWHR. Every year, starting in Jan. 1994, 10 hedge fund portfolios are formed by sorting funds on fund fWHR. The post-formation returns on these 10 portfolios over the next 12 months are linked across years to form a single return series for each portfolio. We then evaluate performance relative to the Fung and Hsieh (2004) model. The sorting procedure accommodates variation in the fund sample as funds enter and drop out of the combined database.

Panel A of Table 2 reveals that hedge funds operated by managers with high fWHR underperform those operated by managers with low fWHR by an economically meaningful 5.30% per year (t-stat = 5.13). After adjusting for co-variation with the Fung and Hsieh (2004) factors, the underperformance decreases marginally to 4.43% per year (t-stat = 5.12).[12] As in the rest of the article, we base statistical inferences on White (1980) heteroscedasticity-consistent standard errors. We note that the average fWHR for the high-fWHR funds in Portfolio 1 is 2.11 and that for the low-fWHR funds in Portfolio 10 is 1.57. Since small hedge funds may not be relevant for large institutional investors, we also conduct the portfolio sort on hedge funds with at least US$50 million of AUM. Panel B of Table 2 indicates that, for such funds, the risk-adjusted outperformance of low-fWHR funds over high-fWHR funds is still economically significant at 4.02% per annum (t-stat = 3.19).

Figure 2 illustrates the monthly cumulative abnormal returns (CARs) from the portfolio of high-fWHR funds (Portfolio 1) and the portfolio of low-fWHR funds (Portfolio 10) from Panel A of Table 2. 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 indicate that the high-fWHR fund portfolio consistently underperforms the low-fWHR fund portfolio over the entire sample period.

Panels A and B of Table 2 appear to suggest that the negative relation between fWHR and fund performance is driven by funds in the top 2 fWHR deciles. However, the funds in the various fWHR deciles may differ significantly in other fund characteristics that can also impact performance.[13] To determine the incremental explanatory power of fWHR on fund performance, we estimate the following pooled OLS regression:

[12]The portfolio sort results are robust to value-weighting the funds within each portfolio. The risk-adjusted spread from the value-weighted sort is −6.29% per annum (t-stat = −4.46). Inferences also do not change when we estimate the factor loadings dynamically over prior 36-month rolling periods. The alpha spread from the sort with dynamic factor loadings is −3.80% per annum (t-stat = −3.45).

[13]Supplementary Material Table S3 indicates that high-fWHR funds tend to charge higher fees and impose shorter lock ups and redemption periods. Moreover, they are more likely to employ leverage and feature high-water marks.

TABLE 2

Portfolio Sorts on Fund fWHR

In Table 2, hedge funds are sorted into 10 portfolios based on the fund facial width-to-height ratio (fWHR). 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 commodity PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Panel A reports the results for the full sample. Panel B reports results for hedge funds with at least US$50m in AUM. Panel C reports results after controlling for the explanatory power of fund characteristics on performance. The *t*-statistics are derived from White (1980) standard errors. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Hedge Fund Portfolio	Excess Return (Annualized)	*t*-Statistic of Excess Return	Alpha (Annualized)	*t*-Statistic of Alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A. Hedge Funds												
Portfolio 1 (high fWHR)	1.50	1.20	−0.25	−0.32	0.27**	0.16**	−1.08**	−1.32*	0.00	0.01**	0.00	0.639
Portfolio 2	4.74**	2.84	2.12*	2.38	0.37**	0.23**	−1.26**	−1.95**	−0.01	0.01**	0.00	0.736
Portfolio 3	7.49**	4.64	4.88**	6.11	0.37**	0.22**	−0.86**	−1.29*	−0.01*	0.01**	0.00	0.768
Portfolio 4	7.09**	5.72	5.28**	7.30	0.27**	0.11**	−0.57*	−1.20**	−0.01*	0.01**	−0.01	0.651
Portfolio 5	7.19**	4.94	4.97**	6.78	0.33**	0.19**	−0.45	−1.41**	−0.01	0.00	0.00	0.761
Portfolio 6	7.77**	5.19	5.65**	6.99	0.32**	0.20**	−0.23	−1.46*	−0.01	0.01**	−0.01	0.724
Portfolio 7	6.32**	5.11	4.55**	6.56	0.24**	0.15**	−0.55	−2.05**	−0.01*	0.00	0.00	0.701
Portfolio 8	7.23**	5.03	5.07**	6.76	0.31**	0.19**	−0.28	−1.24*	−0.01*	0.01**	−0.01	0.742
Portfolio 9	6.32**	4.17	4.16**	4.68	0.30**	0.19**	−0.45	−1.78*	−0.01	0.00	−0.01	0.676
Portfolio 10 (low fWHR)	6.80**	3.75	4.18**	4.02	0.37**	0.24**	−0.57	−2.04*	−0.02	0.00	−0.01	0.689
Spread (1–10)	−5.30**	−5.13	−4.43**	−5.12	−0.10**	−0.09**	−0.52	0.71	0.01	0.00*	0.00	0.324
Panel B. Hedge Funds With at Least US$50m in AUM												
Portfolio 1 (high fWHR)	1.71	1.23	−0.05	−0.05	0.24**	0.13**	−0.77*	−2.05**	−0.02*	0.01**	−0.01	0.531
Portfolio 2	2.42	1.38	0.06	0.05	0.31**	0.12**	−1.38*	−2.06*	−0.02*	0.01**	0.00	0.459
Portfolio 3	6.54**	3.85	3.92**	3.72	0.36**	0.18**	−1.16*	−1.64*	−0.02	0.00	0.00	0.636
Portfolio 4	4.68**	3.67	2.91**	3.49	0.26**	0.10**	−0.64*	−1.49**	−0.01	0.01**	−0.01	0.584
Portfolio 5	7.29**	4.99	5.08**	5.21	0.29**	0.17**	−0.97*	−1.38	−0.02**	0.00	0.00	0.594
Portfolio 6	5.81**	4.09	3.85**	4.10	0.25**	0.17**	−0.64	−2.05**	−0.02	0.00	−0.01	0.616
Portfolio 7	5.54**	4.15	3.67**	4.08	0.22**	0.14**	−0.72*	−2.13**	−0.02**	0.00	−0.01	0.579
Portfolio 8	5.08**	4.07	3.24**	4.19	0.24**	0.12**	−0.44	−1.69**	−0.02**	0.00	0.00	0.648
Portfolio 9	4.92**	3.79	3.12**	3.16	0.21**	0.09**	−0.69	−1.29*	−0.02**	0.00	−0.01	0.459
Portfolio 10 (low fWHR)	6.67**	3.48	3.96**	3.55	0.36**	0.19**	−0.09	−2.49**	−0.03**	0.00	−0.01	0.661
Spread (1–10)	−4.96**	−3.51	−4.02**	−3.19	−0.12**	−0.07	−0.68	0.43	0.01	0.01	−0.01	0.166

(continued on next page)

TABLE 2 (continued)

Portfolio Sorts on Fund fWHR

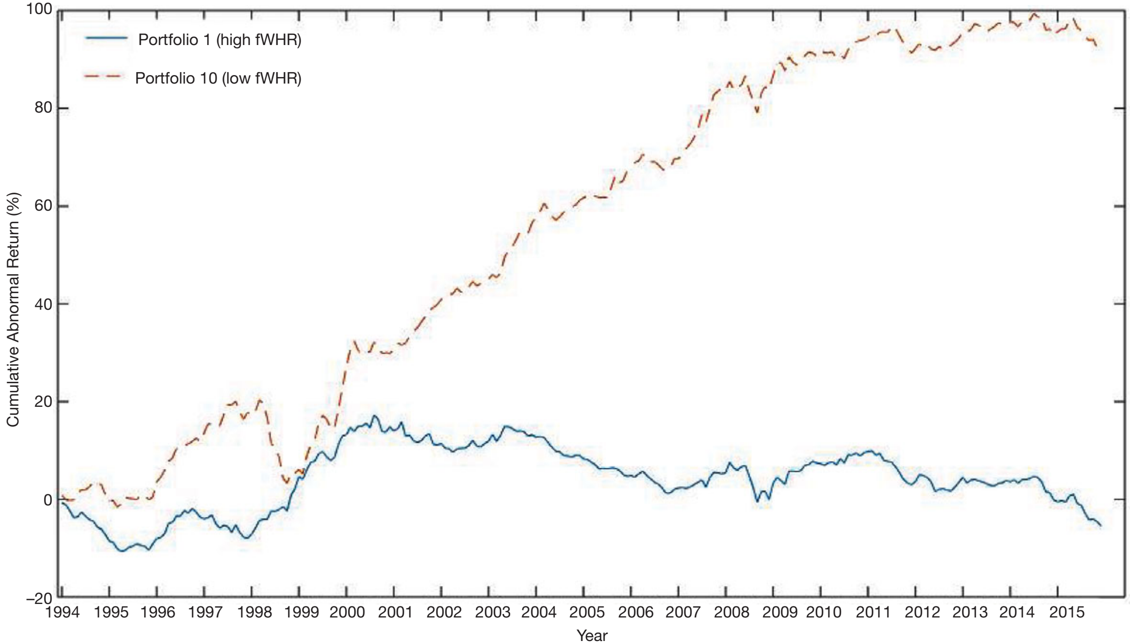
Panel C. Hedge Funds After Controlling for the Explanatory Power of Fund Characteristics

Portfolio 1 (high fWHR)	−0.95	−0.63	−3.21**	−2.97	0.26**	0.22**	−1.67**	−0.44	0.00	0.02**	0.00	0.499
Portfolio 2	1.24	0.75	−1.31	−1.18	0.33**	0.23**	−1.03*	−0.61	0.00	0.00	−0.01	0.581
Portfolio 3	3.49*	2.18	0.74	0.78	0.34**	0.21**	−0.90*	−0.65	−0.01	0.01**	−0.01	0.667
Portfolio 4	1.53	1.25	−0.38	−0.42	0.23**	0.11**	−0.97*	−0.06	−0.01	0.01**	−0.01	0.442
Portfolio 5	2.82*	1.97	0.39	0.40	0.27**	0.15**	−0.92**	−1.07*	−0.02**	0.01**	−0.01	0.568
Portfolio 6	4.11**	2.74	1.76	1.81	0.30**	0.20**	−0.14	−0.13	−0.02	0.01**	−0.01	0.618
Portfolio 7	1.59	1.34	−0.33	−0.39	0.19**	0.17**	−1.07**	−0.92	−0.02*	0.00	0.00	0.507
Portfolio 8	2.17	1.45	−0.19	−0.21	0.28**	0.25**	−0.51	−1.13*	−0.02	0.00*	−0.01	0.686
Portfolio 9	4.69**	3.02	2.11	1.85	0.29**	0.22**	−0.62	0.21	−0.02	0.00	−0.01	0.556
Portfolio 10 (low fWHR)	5.77**	2.85	2.81**	2.06	0.37**	0.27**	−0.49	−1.50	−0.02	0.00	−0.02	0.605
Spread (1–10)	−6.72**	−4.24	−6.02**	−4.28	−0.11**	−0.06	−1.18*	1.06	0.01	0.01*	0.01*	0.257

FIGURE 2

Cumulative Abnormal Returns of Hedge Funds

Figure 2 presents abnormal returns of hedge funds, sorted by fund fWHR. Equal-weighted portfolios of hedge funds are constructed by sorting funds into 10 deciles 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 Jan. 1994 to Dec. 2015.



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$$\begin{aligned}(1)\quad \text{ALPHA}_{im} = {} & \alpha + \beta_1 \text{FWHR}_i + \beta_2 \text{MGTFEE}_i + \beta_3 \text{PERFFEE}_i + \beta_4 \text{HWM}_i \\ & + \beta_5 \text{LOCKUP}_i + \beta_6 \text{LEVERAGE}_i + \beta_7 \text{AGE}_{im-1} \\ & + \beta_8 \text{REDEMPTION}_i + \beta_9 \log\left(\text{FUNDSIZE}_{im-1}\right) \\ & + \sum_k \beta_{10}^k \text{STRATEGYDUM}_i^k + \sum_l \beta_{11}^l \text{YEARDUM}_m^l + \epsilon_{im},\end{aligned}$$

where ALPHA is fund alpha, FWHR is fund fWHR, MGTFEE is management fee, PERFFEE is performance fee, HWM is the high-water mark indicator, LOCKUP is lock-up period, LEVERAGE is the leverage indicator, AGE is fund age since inception, REDEMPTION is redemption period, FUNDSIZE is fund AUM, STRATEGYDUM is the fund strategy dummy, and YEARDUM is the year dummy. Fund alpha is the monthly abnormal return from the Fung and Hsieh (2004) model, where the factor loadings are estimated over the prior 24 months.[14] We estimate the analogous regression on monthly fund excess returns to ensure that our findings are not artifacts of the risk adjustment methodology. Statistical inferences are based on White (1980) robust standard errors clustered by fund and month.

Table 3 corroborates the findings from the portfolio sorts. Specifically, the coefficient estimate on FWHR reported in column 2 indicates that controlling for other factors that could explain fund performance, high-fWHR funds (fWHR = 2.11) underperform low-fWHR funds (fWHR = 1.57) by 2.12% per annum (t-stat = 3.06) after adjusting for risk.[15] The coefficient estimates on the control variables accord with the extant literature; fund size (Berk and Green (2004)) and age (Aggarwal and Jorion (2010)) are linked to poorer performance while share restrictions (Aragon (2007)) are associated with better performance. Figure 3 illustrates the relation between fund fWHR and fund alpha with a binned scatter plot. The downward sloping line of best fit in Figure 3 visually reinforces the findings from the performance regressions.

To check for robustness, we rerun the regressions with FWHR_RANK in place of FWHR. The variable FWHR_RANK is fund fWHR fractional rank determined every month and takes values from 0 to 1. Columns 3 and 4 of Table 3 indicate that our baseline findings are qualitatively unchanged when we analyze relative fWHR. As an additional robustness test, we estimate Fama and MacBeth (1973) regressions on fund performance. The advantage of the Fama–MacBeth procedure is that it accounts for correlation in residuals across different funds within the same month. To adjust for dependence across time, we base statistical inferences on Newey and West (1987) standard errors with a 3-month lag. Columns 5–8 of Table 3 indicate that

[14]Inferences do not change when we use factor loadings estimated over the past 36 months instead.

[15]The dissonance between the underperformance of high-fWHR funds implied by the regression estimates (i.e., 2.12% per annum) and that implied by the portfolio sort (i.e., 4.43% per annum), can be partly explained by the smaller underperformance of high-fWHR funds in the second half of the sample period. We show in Panels C and D of Supplementary Material Table S1 that the risk-adjusted underperformance of high-fWHR versus low-fWHR funds in the first half of our sample period is larger than that in the second half of the sample period. Since there are more fund return observations in the second half of the sample period, this partly explains the difference between the regression and portfolio sort results.

TABLE 3

Multivariate Regressions on Hedge Fund Performance

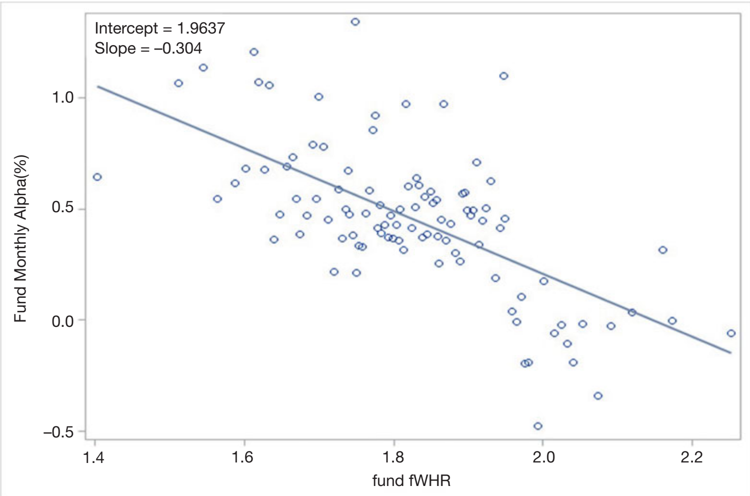
Table 3 reports results from multivariate OLS and Fama and MacBeth (1973) regressions on hedge fund performance. The dependent variables include RETURN, ALPHA, SHARPE, and INFORMATION. RETURN is the monthly hedge fund net-of-fee return. ALPHA is the Fung and Hsieh (2004) 7-factor monthly alpha where factor loadings are estimated over the last 24 months. SHARPE is fund Sharpe ratio or the average monthly fund excess return divided by the standard deviation of monthly fund returns, estimated over each nonoverlapping 24-month period post-fund inception. INFORMATION is the fund information ratio or the average monthly fund alpha divided by the standard deviation of monthly fund residuals, estimated over each nonoverlapping 24-month period post-fund inception. The primary independent variables of interest are fund fWHR (FWHR) and fWHR percentile rank (FWHR_RANK), which is computed every year and takes values from 0 to 1. The other independent variables include fund management fee (MGTFEE), performance fee (PERFFEE), high-water mark indicator (HWM), lock-up period in years (LOCKUP), leverage indicator (LEVERAGE), 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 for the OLS regressions on fund return and alpha, and clustered by fund for the OLS regressions on fund Sharpe ratio and information ratio. They are derived from Newey and West (1987) standard errors with a 3-month lag for the Fama and MacBeth (1973) regressions. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

	OLS Regressions				Fama–MacBeth Regressions				OLS Regressions			
	RETURN	ALPHA	RETURN	ALPHA	RETURN	ALPHA	RETURN	ALPHA	SHARPE	INFORMATION	SHARPE	INFORMATION
Independent Variable	1	2	3	4	5	6	7	8	9	10	11	12
FWHR	−0.384*	−0.327**			−0.341*	−0.323*			−0.211**	−0.417**		
	(−2.34)	(−3.06)			(−1.99)	(−2.48)			(−3.35)	(−3.81)		
FWHR_RANK			−0.187**	−0.186**			−0.169*	−0.179**			−0.136**	−0.277**
			(−2.67)	(−3.63)			(−2.20)	(−3.21)			(−4.03)	(−4.31)
MGTFEE	0.100	0.093*	0.100	0.092*	0.107*	0.108**	0.106*	0.108**	0.017	−0.040	0.015	−0.043
	(1.83)	(2.11)	(1.83)	(2.09)	(2.42)	(2.94)	(2.41)	(2.93)	(0.78)	(−1.11)	(0.72)	(−1.18)
PERFFEE	−0.008	0.001	−0.008	0.001	0.000	0.004	−0.000	0.003	−0.002	0.012	−0.002	0.012
	(−1.92)	(0.38)	(−1.91)	(0.37)	(0.01)	(1.19)	(−0.05)	(1.09)	(−0.76)	(1.56)	(−0.76)	(1.57)
HWM	0.162**	0.153**	0.158**	0.150**	0.117*	0.148**	0.111*	0.143**	−0.007	0.009	−0.010	0.004
	(3.49)	(3.85)	(3.36)	(3.77)	(2.39)	(4.60)	(2.27)	(4.54)	(−0.14)	(0.10)	(−0.18)	(0.05)
LOCKUP	0.062	0.022	0.063	0.023	0.040	0.054	0.037	0.053	−0.002	−0.154	−0.001	−0.152
	(1.56)	(0.60)	(1.58)	(0.63)	(0.72)	(1.38)	(0.67)	(1.37)	(−0.09)	(−1.83)	(−0.05)	(−1.82)
LEVERAGE	0.011	0.031	0.011	0.032	−0.045	0.019	−0.047	0.018	−0.041	−0.078	−0.040	−0.074
	(0.32)	(0.83)	(0.31)	(0.86)	(−1.07)	(0.59)	(−1.10)	(0.56)	(−1.76)	(−1.78)	(−1.68)	(−1.71)
AGE	−0.008**	−0.007**	−0.008**	−0.007**	−0.008	−0.009**	−0.008	−0.008**	−0.001	−0.005	−0.001	−0.005
	(−2.66)	(−2.82)	(−2.69)	(−2.81)	(−1.47)	(−3.22)	(−1.51)	(−3.09)	(−0.46)	(−0.51)	(−0.45)	(−0.50)
REDEMPTION	0.014*	0.003	0.015*	0.003	0.017**	0.001	0.019**	0.001	0.004	−0.004	0.004	−0.004
	(2.40)	(0.54)	(2.41)	(0.54)	(2.80)	(0.24)	(2.91)	(0.30)	(1.62)	(−0.63)	(1.54)	(−0.71)
log(FUNDSIZE)	−0.066**	−0.004	−0.066**	−0.003	−0.090**	−0.012	−0.089**	−0.011	0.000	0.023	0.001	0.024
	(−4.04)	(−0.31)	(−4.00)	(−0.24)	(−5.61)	(−1.19)	(−5.49)	(−1.04)	(0.05)	(1.12)	(0.13)	(1.16)
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.029	0.016	0.029	0.016	0.090	0.064	0.089	0.063	0.073	0.049	0.075	0.050
No. of obs.	133,906	102,026	133,906	102,026	133,906	102,026	133,906	102,026	5,135	5,135	5,135	5,135

FIGURE 3

Fund Alpha Against Fund fWHR

Figure 3 shows a binned scatter plot of fund alpha against fund fWHR. Fund fWHR is the average of facial width-to-height ratios of the managers operating the fund. Only male managers are included in the sample. Fund alpha is the monthly abnormal return from the Fung and Hsieh (2004) model, where the factor loadings are estimated over the prior 24 months. Fund monthly alpha observations are sorted into 100 groups based on fund fWHR. The scatter plot graphs the average fund fWHR for each group against its average monthly alpha. The line represents the line of best fit through the scatter plot. The sample period is from Jan. 1994 to Dec. 2015.



our results are robust to alternative specifications. To ensure that our findings are not driven by time-varying leverage, we estimate analogous regressions on fund Sharpe ratio and information ratio. Columns 9–12 of Table 3 reveal that high-fWHR funds deliver lower Sharpe and information ratios than do low-fWHR funds.

Next, we revisit the relation between fWHR and fund performance observed from the portfolio sorts. We perform the analogous sort based on fWHR but report, in Panel C of Table 2, the residuals from the regression of excess returns on the non-fWHR fund characteristics from equation (1). The pattern of residuals showcased in Panel C reveals that after adjusting for other fund characteristics that can explain fund performance there is a more linear relation between fund performance and fWHR. To confirm, we perform the Spearman nonparametric test on the rank ordering of the performance measures in Panel C. The null hypothesis that the performance measures are randomly ordered can be rejected at the 5% significance level regardless of whether we analyze excess returns or alpha, thereby suggesting that our findings are not driven by the extremely high fWHR observations.

B. Fund Trading Behavior

How does manager fWHR engender fund underperformance? Since fWHR correlates positively with aggression (Carré and McCormick (2008), Carré, McCormick, and Mondloch (2009)), high-fWHR managers may load more on lottery-like stocks and trade stocks more actively. To the extent that fWHR is associated with competitiveness (Tsujimura and Banissy (2013)) and competitive individuals are

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driven by an aversion to losses, fWHR may relate to the disposition effect. As Odean (1998), Kumar (2009), and Bali, Cakici, and Whitelaw (2011) show, a preference for lotteries and the disposition effect could hurt investment performance.

To investigate, we first construct 4 trading behavior measures from hedge fund firm 13F long-only quarterly stock holdings: LOTTERY, DISPOSITION, NONSPRATIO, and ACTIVESHARE. LOTTERY is the maximum daily stock return over the past month averaged across all stocks held as per Bali, Cakici, and Whitelaw (2011). DISPOSITION is the difference between the percentage of gains realized (PGR) 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 (Cremers and Petajisto (2009)) relative to the S&P 500. The last 2 measures capture active trading.

Next, we estimate multivariate regressions on the quarterly trading behavior measures with the set of controls used in equation (1). Table 4 indicates that fund fWHR is associated with a preference for lottery-like stocks, a tendency to hold on to their losses, and active trading. Do such trading behaviors in turn engender underperformance? To investigate, we estimate the equation (1) performance regressions with the trading behavior measures averaged over the previous 4 quarters as additional independent variables. Supplementary Material Table S4 reveals that such trading behaviors partly account for the negative relation between fWHR and fund performance.[16]

C. Fund Operational and Investment Risk

According to the extant literature, fWHR predicts unethical behavior in men (Haselhuhn and Wong (2012), Geniole et al. (2014)). In the hedge fund arena, unethical behavior can manifest as increased operational risk. Moreover, Kamiya, Kim, and Park (2019) show that high-fWHR firm CEOs take on more financial risk. In this section, we explore the relation between fWHR and fund risk attributes.

To study operational risk, we first analyze fund termination, since Brown et al. (2009) find that operational risk is more important than financial risk for explaining fund failure. In that effort, we estimate a multivariate logit regression on an indicator variable, TERMINATION1, that takes a value of 1 when a fund stops reporting returns for that month and states that it has liquidated. We limit the analysis to TASS and HFR funds since only TASS and HFR provide the reason for why a fund stopped reporting returns. The regression includes as controls those featured in equation (1) as well as past 24-month fund returns.

[16]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 between risk-adjusted performance and Active Share is not always robust even for mutual funds. For example, Busse, Jiang, and Tang (2021) show that the significant relation between Active Share and the Carhart (1997) 4-factor alpha in mutual funds is driven by the characteristic-related component of performance (Daniel, Grinblatt, Titman, and Wermers (1997)) rather than by fund skill. Similarly, Frazzini, Friedman, and Pomorski (2016) conclude that Active Share is not an appropriate measure of managerial skill for mutual funds.

TABLE 4

Multivariate Regressions on Hedge Fund Trading Behavior Measures

Table 4 reports results from multivariate regressions on quarterly hedge fund trading behavior measures. The dependent variables include LOTTERY, DISPOSITION, NONSPRATIO, and ACTIVESHARE. LOTTERY is the maximum daily stock return over the past 1 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 fund fWHR (FWHR). The other independent variables include fund management fee (MGTFEE), performance fee (PERFFEE), high-water mark indicator (HWM), lock-up period in years (LOCKUP), leverage indicator (LEVERAGE), 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 Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Independent Variable	Dependent Variable			
	LOTTERY	DISPOSITION	NONSPRATIO	ACTIVESHARE
	1	2	3	4
FWHR	0.060**	0.074**	0.142**	0.097**
	(3.82)	(3.86)	(5.13)	(4.91)
MGTFEE	0.000	0.004	−0.031**	−0.002
	(0.03)	(0.74)	(−3.66)	(−0.30)
PERFFEE	0.001	0.001	0.002	−0.000
	(1.93)	(1.68)	(1.80)	(−0.49)
HWM	0.006	−0.002	−0.021	0.026**
	(1.05)	(−0.26)	(−1.78)	(3.13)
LOCKUP	0.003	−0.007	−0.008	−0.003
	(0.55)	(−0.85)	(−0.63)	(−0.40)
LEVERAGE	0.001	0.007	0.029**	0.003
	(0.16)	(1.13)	(2.93)	(0.52)
AGE	0.001	−0.001	0.005	0.002
	(0.23)	(−0.45)	(1.12)	(0.73)
REDEMPTION	0.003*	−0.003**	−0.003	−0.004**
	(2.23)	(−2.65)	(−1.44)	(−3.71)
log(FUNDSIZE)	0.003**	0.002	0.011**	−0.001
	(3.36)	(1.10)	(4.68)	(−0.83)
Strategy fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.050	0.016	0.048	0.026
No. of obs.	23,025	19,645	20,405	20,683

Column 1 of Table 5 indicates that, controlling for past fund performance and other factors that can explain fund termination, high-fWHR managers are more likely to terminate their funds. The marginal effect suggests that high-fWHR funds (fWHR = 2.10) are 3.09 percentage points more likely to terminate in any given year than are low-fWHR funds (fWHR = 1.57).[17] These results are economically meaningful given that the unconditional probability of fund termination in any given year is 6.12%. As column 2 of Table 5 shows, inferences remain unchanged when we estimate a semi-parametric Cox hazard rate regression on fund termination and report the hazard ratios. Columns 3 and 4 indicate that inferences do not change when we employ the Liang and Park (2010) criteria to infer fund failure. Liang and Park (2010) classify as failed funds those that i) stopped

[17]The marginal effect reported in column 1 of Table 5 reveals that a 1-unit increase in FWHR is associated with a 0.5 percentage point increase in the probability of termination in any given month or a $100 \times \left(1-(1-0.005)^{12}\right) = 5.84$ percentage point increase in probability of termination in any given year.

TABLE 5

Multivariate Regressions on Hedge Fund Operational and Investment Risk Metrics

Table 5 reports results from multivariate regressions on hedge fund risk metrics. The dependent variables include operational risk metrics such as fund termination indicator1 (TERMINATION1 and TERMINATION2), Form ADV violation indicator (VIOLATION), and ω-Score (OMEGA), as well as investment risk metrics such as total risk (RISK), downside risk (DOWNSIDERISK), downside beta (DOWNSIDEBETA), maximum monthly loss (MAXLOSS), and maximum drawdown (MAXDRAWDOWN). TERMINATION1 takes a value of 1 after a hedge fund stops reporting and states that it has liquidated that month. TERMINATION2 takes a value of 1 when it has failed that month based on the Liang and Park (2010) criteria. VIOLATION takes a value of 1 when the hedge fund manager reports on Item 11 of Form ADV that the manager has been associated with a regulatory, civil, or criminal violation. OMEGA is an operational risk instrument derived from fund performance, volatility, age, size, fee structure, and other fund characteristics as per Brown et al. (2009). RISK is the standard deviation of monthly hedge fund returns. DOWNSIDERISK is the downside deviation of monthly hedge fund returns where the minimum acceptable return is 0. DOWNSIDEBETA is downside beta relative to the S&P 500 index. MAXLOSS is the maximum monthly loss. MAXDRAWDOWN is the maximum cumulative loss. The investment risk metrics are estimated over each nonoverlapping 24-month period after fund inception. To maximize the number of observations, the computation of downside beta leverages on observations derived from noncontiguous 24-month periods. The primary independent variable of interest is fund fWHR (FWHR). The other independent variables include fund management fee (MGTFEE), performance fee (PERFFEE), high-water mark indicator (HWM), lock-up period in years (LOCKUP), leverage indicator (LEVERAGE), 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 regressions on TERMINATION also control for fund return averaged over the last 24 months (RETURN). The coefficient estimates for these variables are omitted for brevity. The *t*-statistics or *z*-statistics (in the case of the Cox regression) in parentheses are derived from robust standard errors that are clustered by fund. The marginal effects are in square brackets. For the Cox regressions, we report the hazard ratios. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

	Operational Risk Metrics						Investment Risk Metrics				
	TERMINATION1		TERMINATION2		VIOLATION	OMEGA	RISK	DOWNSIDE-RISK	DOWNSIDE-BETA	MAXLOSS	MAXDRAW-DOWN
	Logit	Cox	Logit	Cox	OLS	OLS	OLS	OLS	OLS	OLS	
Independent Variable	1	2	3	4	5	6	7	8	9	10	11
FWHR	0.761**	2.122**	1.317**	3.908**	1.477**	0.310**	−0.389	1.726**	0.252**	3.109**	3.092*
	(4.13)	(4.14)	(4.79)	(5.14)	(3.05)	(4.05)	(−0.72)	(3.54)	(2.86)	(3.08)	(2.17)
	[0.005]		[0.003]		[0.307]						
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.127	0.098	0.134	0.169	0.025	0.777	0.169	0.178	0.109	0.181	0.180
No. of obs.	129,653	129,653	144,361	146,448	973	589	5,202	5,019	2,822	5,202	5,202

reporting to the databases, ii) reported a negative average return over the 6-month period before dropping out, and iii) reported a drop in AUM over the 12-month period before dropping out.

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 are reported as Item 11 disclosures on Form ADV.[18] To explore the relation between fWHR and violations of expected standards of business conduct, we estimate multivariate logit regressions on an indicator variable VIOLATION that takes a value of 1 when a fund manager makes an Item 11 Form ADV disclosure. The marginal effect in Column 5 of Table 5 indicates that high-fWHR funds (fWHR = 2.10) are 16.27 percentage points more likely to report violations than are low-fWHR funds (fWHR = 1.57).

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, fee structure, and other fund characteristics that Brown et al. (2009) show is useful for predicting hedge fund failures.[19] Next, we estimate a multivariate regression on OMEGA or fund ω-Score with FWHR as an independent variable and with the control variables from equation (1). Column 6 of Table 5 indicates that high-fWHR funds exhibit higher ω-Scores.

To investigate investment risk, we estimate regressions on fund total risk (RISK), downside risk (DOWNSIDERISK), downside beta (DOWNSIDEBETA), maximum loss (MAXLOSS), and maximum drawdown (MAXDRAWDOWN). RISK is standard deviation of monthly hedge fund returns. DOWNSIDERISK is downside deviation of monthly hedge fund returns where the minimum acceptable return is 0. DOWNSIDEBETA is downside beta relative to the S&P 500 index, MAXLOSS is maximum monthly loss. MAXDRAWDOWN is maximum cumulative loss. The risk measures are estimated over each nonoverlapping 24-month period post-fund inception. The analysis of downside deviation, downside beta, maximum loss, and maximum drawdown provides texture on the left tail of the return distribution. Columns 7–11 of Table 5 indicate that while high-fWHR funds do not deliver more volatile returns, their returns exhibit greater downside deviations, higher downside betas, larger maximum monthly losses, and steeper maximum drawdowns, suggesting that they bear more left tail risk.

[18]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.

[19]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). 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).

D. Fund Asset-Liability Mismatch

Given their aggressive tendencies, high-fWHR managers may take on too much liquidity risk *relative* to their share restrictions. Specifically, they may load up on liquidity risk to earn the liquidity risk premium (Pástor and Stambaugh (2003), Sadka (2010)) while granting favorable redemption terms to their investors to attract capital. The resultant asset-liability mismatch could translate into fire sales and purchases following investor redemptions and subscriptions (Coval and Stafford (2007)).

Consistent with this intuition, we find indeed that high-fWHR funds take on more liquidity risk while offering better redemption terms to their investors. Specifically, the coefficient estimate on FWHR is positive in the univariate regression on fund Pástor and Stambaugh (2003) liquidity beta, estimated over all nonoverlapping 24-month periods post-fund inception, but negative in the univariate regression on fund redemption period. Both these estimates are statistically significant at the 1% level.

To investigate whether this translates into asset fire sales and purchases, we follow Teo (2011) and sort hedge funds every month into decile portfolios based on last month's fund flow. We then evaluate performance relative to the Fung and Hsieh (2004) model. We do this separately for high-fWHR and low-fWHR funds, which are those in the top 30th and bottom 30th fund fWHR percentiles, respectively.

Table 6 supports the view that high-fWHR funds are more susceptible to fire sales and purchases than are low-fWHR funds. For high-fWHR funds, those that experience strong inflows subsequently outperform in the next month those that experience strong outflows by 5.88% per annum (t-stat = 2.32) after adjusting for risk. Conversely, for low-fWHR funds, the corresponding spread is only −0.20% per annum (t-stat = −0.08).

The time-series variation in the monthly abnormal spread returns from the flow sort for high-fWHR funds accords with the fire sales and purchases view. When markets are bereft of liquidity (i.e., when the Pástor and Stambaugh (2003) aggregated liquidity measure falls below its 20th percentile level), the average abnormal spread return is an impressive 7.87% per annum. When markets are flushed with liquidity (i.e., when the Pástor and Stambaugh (2003) aggregated liquidity measure rises above its 80th percentile level), the average abnormal spread return is only 0.52% per annum. Consistent with the Brunnermeier and Pedersen (2009) view that fire sales and purchases should be more rampant when funding liquidity is low, we find that the abnormal spread is higher when the Treasury–Eurodollar spread is wide and aggregate hedge fund flows are low. These results are available upon request.

E. Fund Marketing Intensity

Facial width has been associated with stronger achievement drive among U.S. presidents (Lewis, Lefevre, and Bates (2012)) and Chinese sell-side analysts (He et al. (2019)). In the hedge fund context, a stronger achievement drive could translate into greater capital raising intensity, which would have implications for fund flow, size, and fee revenues.

TABLE 6

Portfolio Sorts on Hedge Fund Flow

In Table 6, hedge funds are sorted into 10 portfolios based on fund flow last month. 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 commodity PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Fund fWHR is the average facial width-to-height ratio or fWHR of the manager operating a hedge fund. High-fWHR and low-fWHR funds are those in the top and bottom 30th percentiles based on fund fWHR, respectively. The *t*-statistics are derived from White (1980) standard errors. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Hedge Fund Portfolio	Excess Return (Annualized)	*t*-Statistic of Excess Return	Alpha (Annualized)	*t*-Statistic of Alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A. High-fWHR Hedge Funds												
Portfolio 1 (high flow)	8.36**	3.90	6.03**	3.55	0.34**	0.16**	−1.46*	−1.67	−0.01	0.03**	0.01	0.419
Portfolio 2	4.02	1.71	1.76	0.99	0.31**	0.24**	−2.65**	−4.34**	0.01	0.01	−0.01	0.471
Portfolio 3	5.94**	3.33	3.82**	3.05	0.32**	0.16**	−1.00*	−1.53*	−0.01	0.02**	−0.01	0.544
Portfolio 4	5.79**	3.26	3.72**	3.02	0.33**	0.18**	−1.20*	−1.28*	0.00	0.02**	−0.00	0.552
Portfolio 5	3.25	1.45	0.96	0.61	0.42**	0.17**	−0.94	−1.77*	0.01	0.02	−0.00	0.545
Portfolio 6	2.62	1.03	−0.37	−0.2	0.42**	0.33**	−0.90	−0.68	−0.00	0.01	0.01	0.509
Portfolio 7	1.71	0.95	−0.36	−0.32	0.30**	0.16**	−0.28	−2.18**	−0.02*	0.01*	0.00	0.627
Portfolio 8	3.95	1.88	1.28	1.05	0.37**	0.23**	−1.61**	−3.16**	−0.01	0.02**	−0.01	0.688
Portfolio 9	4.77**	2.53	2.98*	2.32	0.35**	0.11**	−1.19*	−2.61**	0.01	0.03**	−0.01	0.570
Portfolio 10 (low flow)	0.66	0.27	0.15	0.09	0.38**	0.30**	−2.53**	−3.17**	−0.00	0.02*	0.00	0.539
Spread (1–10)	7.70*	2.37	5.88*	2.32	−0.04	−0.14	1.13	1.50*	−0.01	0.01	0.01	0.058
Panel B. Low-fWHR Hedge Funds												
Portfolio 1 (high flow)	8.68**	3.74	5.66**	3.39	0.39**	0.30**	−1.87**	−0.87	−0.00	0.00	0.00	0.519
Portfolio 2	7.05**	3.66	4.64**	3.51	0.31**	0.18**	−1.15*	−2.48**	−0.02*	0.01	0.01	0.562
Portfolio 3	5.96**	2.84	3.42**	2.42	0.33**	0.19**	−0.39	−1.93**	−0.03**	0.02*	−0.02	0.578
Portfolio 4	9.39**	4.27	7.25**	4.45	0.30**	0.24**	−0.88	−2.57**	−0.01	0.01	−0.01	0.492
Portfolio 5	5.94**	2.59	3.58*	2.36	0.38**	0.24**	−0.51	−2.37**	−0.00	0.01	−0.02	0.597
Portfolio 6	4.92**	2.44	2.69	1.90	0.37**	0.24**	0.19	0.07	−0.01	0.02*	0.01	0.543
Portfolio 7	5.92**	3.26	3.56**	2.97	0.31**	0.14**	−0.20	−1.19*	−0.03**	0.01	−0.01	0.597
Portfolio 8	4.66**	2.26	2.07	1.44	0.32**	0.21**	−0.58	−1.65*	−0.03**	0.02*	−0.01	0.548
Portfolio 9	6.16**	2.68	3.72*	2.40	0.41**	0.15**	−0.75	−2.48**	−0.01	0.01	−0.01	0.578
Portfolio 10 (low flow)	7.78**	3.06	5.88**	2.92	0.35**	0.18**	−0.68	−2.95**	0.01	0.01	−0.02	0.418
Spread (1–10)	0.90	0.26	−0.20	−0.08	0.04	0.12	−1.19*	2.08*	−0.01	−0.01	0.02	0.047

To investigate, we estimate multivariate regressions analogous to equation (1) on hedge fund annual flow with fund fWHR as the independent variable of interest. As in Siri and Tufano (1998), we control for fund performance rank based on past 12-month return (RANK12). For robustness, we also estimate regressions that control for fund performance rank based on past 24-month return (RANK24), past 12- and 24-month CAPM alpha (RANK12_CAPM and RANK24_CAPM), and past 12- and 24-month Fung and Hsieh (2004) alpha (RANK12_FH and RANK24_FH).[20]

The coefficient estimate on FWHR in column 1 of Table 7 indicates that after adjusting for other factors, high-fWHR funds (fWHR = 2.10) attract 5.14% more flows per year than do low-fWHR funds (fWHR = 1.57). Consistent with Agarwal, Green, and Ren (2018), fund flow is positively related to past fund performance. Columns 2–6 of Table 7 reveal that the relation between fWHR and fund flow is robust to alternative specifications.

Does the positive relation between fund fWHR and fund flow also manifest in the univariate setting? What are its implications for fund fee revenues and AUM? To address these questions, every Jan. 1st, we sort hedge funds into 10 portfolios based on fund fWHR. The post-formation annual fund flows, annual fund fee revenues, and end-of-the-year fund AUM of these 10 portfolios are linked across years to form a single series for each portfolio. We report the average annual fund flow, annual fund fee revenue, and end-of-the-year fund AUM for each portfolio in columns 1–3 of Table 8, as well as the differences in these fund characteristics between the high- and low-fWHR fund portfolios. The results indicate that, despite underperforming their low-fWHR competitors, high-fWHR funds garner 5.62% more annual flows, harvest US$3.16 million more fee revenues per year, and oversee US$208.54 million more assets.

Do the higher flows that high-fWHR managers attract stem from greater marketing intensity? We propose 3 novel measures of marketing effort: i) the number of commercial hedge fund databases that a fund reports returns to ii) the number of duplicate share classes for the fund, and iii) the number of hedge fund conferences that a fund manager participates in.[21] In line with the marketing intensity view, columns 4–6 of Table 8 reveal that high-fWHR managers promote their funds more aggressively by reporting to more databases, offering more duplicate share classes, and speaking at more conferences. By doing so, they reduce investors' search and entry costs.

We next examine the degree to which the marketing intensity proxies explain the positive association between fund flow and fund fWHR by including in the flow regressions 3 additional independent variables: the number of commercial databases that a fund reports returns to last year (NDATABASE), the number of duplicate share classes offered by the fund management company for that fund last

[20]We control for 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.

[21]We thank Narayan Naik for suggesting conference participation as a proxy for marketing intensity. We distinguish between conference attendance and participation. By our definition, a manager participates in a conference if his name appears on the conference program. This typically implies that he is either a speaker, panelist, or moderator at the conference. We collect conference participation data via an Internet search.

TABLE 7

Multivariate Regressions on Hedge Fund Flow

Table 7 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 primary independent variable of interest is fund fWHR (FWHR). The independent variables include RANK12, RANK12_CAPM, RANK12_FH, RANK24, RANK24_CAPM, and RANK24_FH. The variable RANK12 is fund's fractional rank which represents its percentile performance based on its past 12-month return relative to other funds and ranges from 0 to 1, as in Siri and Tufano (1998). RANK12_CAPM is fund's fractional rank based on past 12-month CAPM alpha. RANK12_FH is fund's fractional rank based on its past 12-month Fung and Hsieh (2004) alpha. 12-month CAPM alpha is the monthly fund abnormal return relative to the CAPM averaged over the last 12 months, where the betas are estimated over the last 24 months. 12-month Fung and Hsieh (2004) alpha is computed analogously. The independent variables RANK24, RANK24_CAPM, and RANK24_FH are the 24-month analogs of RANK12, RANK12_CAPM, and RANK12_FH. The other independent variables include fund management fee (MGTFEE), performance fee (PERFFEE), high-water mark indicator (HWM), lock-up period in years (LOCKUP), leverage indicator (LEVERAGE), 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 for these variables are omitted for brevity. Columns 7–12 feature regressions with 3 additional independent variables that capture fund marketing intensity: the number of commercial databases that a fund reports returns to at the end of last year (NDATABASE), the number of duplicate share classes offered for that fund at the end of last year (NSHARECLASS), and the number of conferences that the fund manager participated in over the last 3 years (NCONFERENCE). The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Independent Variable	Dependent Variable = FLOW											
	1	2	3	4	5	6	7	8	9	10	11	12
FWHR	9.694**	11.177**	10.268**	11.381**	10.337**	11.016**	5.534	7.003	6.097	7.212*	6.172	6.836
	(2.65)	(3.14)	(2.80)	(3.16)	(2.67)	(2.91)	(1.49)	(1.94)	(1.64)	(1.98)	(1.58)	(1.78)
NDATABASE							1.555**	1.399*	1.714**	1.798**	1.708**	1.622**
							(2.73)	(2.45)	(3.16)	(3.34)	(3.13)	(2.96)
NSHARECLASS							1.134*	1.105*	0.816	0.722	0.912*	0.800
							(2.42)	(2.32)	(1.72)	(1.59)	(2.07)	(1.74)
NCONFERENCE							1.258	1.222	1.250	1.269	1.380*	1.410*
							(1.69)	(1.72)	(1.81)	(1.83)	(2.07)	(2.18)
RANK12	32.974**						33.106**					
	(10.27)						(10.12)					
RANK24		42.589**						42.719**				
		(13.56)						(13.38)				
RANK12_CAPM			40.533**						40.696**			
			(10.51)						(10.53)			
RANK24_CAPM				45.355**						45.485**		
				(12.64)						(12.67)		
RANK12_FH					44.159**						44.372**	
					(12.92)						(12.90)	
RANK24_FH						48.435**						48.609**
						(14.19)						(14.09)
Other fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.081	0.100	0.081	0.088	0.084	0.090	0.081	0.100	0.080	0.087	0.084	0.090
No. of obs.	10,417	10,417	10,298	10,298	10,298	10,298	10,417	10,417	10,298	10,298	10,298	10,298

TABLE 8

Fund Characteristics of Portfolios Sorted on Fund fWHR

Every Jan. 1st, hedge funds are sorted into 10 portfolios based on the average facial width-to-height ratio (fWHR) of the managers operating the funds. The post-formation annual fund flows in percentage, annual fund fee revenues in US$m, end-of-the-year fund AUM in US$m, and marketing intensity proxies of these 10 portfolios during the year are linked across years to form a single series for each portfolio. The marketing intensity proxies in Table 8 include i) the number of commercial databases that the fund reports to at the end of the year, ii) the number of duplicate share classes offered for the fund at the end of the year, and iii) number of conferences that the fund manager participates in during the year. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Hedge Fund Portfolio	Annual Fund Flow (%) (1)	Annual Fee Revenue (US$m) (2)	Fund AUM (US$m) (3)	Number of Fund Databases (4)	Number of Duplicate Share Classes (5)	Number of Conferences (6)
Portfolio 1 (high fWHR)	8.98	6.12	487.93	1.76	0.50	0.040
Portfolio 2	5.82	4.88	474.36	1.77	0.45	0.036
Portfolio 3	9.51	4.95	586.77	1.69	0.45	0.044
Portfolio 4	8.33	3.76	381.98	1.68	0.38	0.009
Portfolio 5	8.27	3.54	539.96	1.73	0.33	0.038
Portfolio 6	7.27	4.08	374.01	1.66	0.32	0.015
Portfolio 7	7.32	4.83	416.76	1.58	0.39	0.002
Portfolio 8	7.54	3.41	423.58	1.66	0.26	0.006
Portfolio 9	7.40	2.49	267.86	1.68	0.32	0.005
Portfolio 10 (low fWHR)	3.36	2.96	279.39	1.53	0.23	0.004
Spread (1–10)	5.62**	3.16**	208.54**	0.23**	0.27*	0.036**

year (NSHARECLASS), and the number of investment conferences that the fund manager participated in over the last 3 years (NCONFERENCE). Column 7 of Table 7 indicates that marketing intensity explains about 42.91% of the coefficient estimate on FWHR in the flow regression with RANK12 as an independent variable. Moreover, columns 7–12 of Table 7 reveal that with the inclusion of the marketing intensity proxies, the coefficient estimates on FWHR are no longer statistically significant at the 5% level for 5 of the 6 regression specifications considered. Consistent with our intuition, all 3 marketing intensity proxies relate positively to fund flow, although the relation with flow is most robust for NDATABASE.

F. Endogeneity

Unobserved factors unrelated to testosterone but related to fWHR may affect investment performance. Self-disciplined managers could exercise more or watch their diets more closely, and therefore, be slimmer. While we have removed managers with significant facial adiposity from the sample, facial width could still positively relate to facial adiposity and, therefore, negatively relate to self-discipline.[22] Alternatively, people may treat high-fWHR men with fear and mistrust even though fWHR does not by itself engender aggression and deception. Such stereotypes of wide-faced men may lead to a self-fulfilling prophecy whereby these men become aggressive and deceptive as a reaction to their negative social environment.

[22]Some studies argue that the presence of facial fat may conceal variation in craniofacial dimensions (Coetzee, Chen, Perrett, and Stephen (2010), Kramer, Jones, and Ward (2012), and Lefevre et al. (2013)). Facial adiposity, especially around the upper cheek area, could inflate our measurement of facial width. Therefore, by exercising and dieting, fund managers could potentially reduce fWHR, even though their facial bone structures do not change.

To address such endogeneity concerns, we leverage on 2 personal events that sharply reduce circulating testosterone in men: marriage and fatherhood. Mazur and Michalek (1998) and Holmboe et al. (2017) show that married men experience substantially greater declines in testosterone levels relative to unmarried men while Gettler et al. (2011) find that testosterone declines rapidly after men become fathers. Under the circulating testosterone view, given the higher *reactive* testosterone levels of high-fWHR men, marriage and fatherhood should exert a greater impact on testosterone for high-fWHR men than for low-fWHR men. This hypothesis also follows Gettler et al. (2011). They conclude that human males have an evolved neuroendocrine architecture that is responsive to committed parenting, supporting the role of men as direct caregivers and thereby increasing reproductive fitness. Therefore, given their higher *baseline* levels of testosterone, high-fWHR men should benefit most from greater reductions in testosterone to prime them to be supportive partners and fathers. Consistent with this view, Berg and Wynne-Edwards (2001) find that the drop in testosterone levels post fatherhood occurs only for men with high baseline (i.e., pre-birth) levels of testosterone and is absent for men with low baseline levels of testosterone.

To investigate, we first collect data on marriage and divorce for managers based in the 13 U.S. states that publicly disclose marital records.[23] We obtain marital records for 127 out of the 457 fund managers that operate in the 13 states. Separately, we assemble data on the children of male fund managers from the LexisNexis database. Of the managers in our sample with fWHR information, 811 managers who manage 1,209 funds can be found on the LexisNexis database. Offspring data, including birth dates, are available for 154 of these managers who father 158 children and operate 277 funds. Next, we construct 2 indicator variables, MARRIED and FATHER, that take values of 1 for managers that are married and managers that are fathers, respectively. We then estimate 2 sets of regressions on fund performance, analogous to equation (1), that include as additional independent variables MARRIED and FATHER as well as their interactions with FWHR and FWHR_RANK.

Table 9 reveals that both marriage and fatherhood attenuate the underperformance of high-fWHR managers. The coefficient estimates on the interactions of MARRIED and FATHER with FWHR_RANK indicate that the underperformance of top-decile fWHR funds relative to bottom-decile fWHR funds is reduced by a risk-adjusted 5.38% per annum for married managers and by a risk-adjusted 5.18% per annum for managers with children. These findings are difficult to reconcile with an explanation based on self-discipline since it is not clear why managers with greater self-control should perform relatively worse following marriage and fatherhood. These results are also hard to square with a story based on the nurturing effects of stereotypes since generalizations of wide-faced men should not abruptly change when they get married or father children. Moreover, any character traits, that emerge from the reaction to such stereotypes, should be relatively persistent.

[23]The 13 states 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.

TABLE 9

Endogeneity Tests with Major Personal Events

Table 9 reports results from multivariate OLS regressions on hedge fund performance. The dependent variables include RETURN and ALPHA where RETURN is the monthly hedge fund net-of-fee return and ALPHA is the Fung and Hsieh (2004) monthly alpha with factor loadings estimated over the last 24 months. The primary independent variables of interest are fund fWHR (FWHR), fWHR percentile rank that is computed every year and takes values from 0 to 1 (FWHR_RANK), an indicator variable that takes a value of 1 when the fund manager is married (MARRIED), and an indicator variable that takes a value of 1 when the fund manager is a father (FATHER) as well as the interactions of FWHR and FWHR_RANK with MARRIED and FATHER. The other independent variables include fund management fee (MGTFEE), performance fee (PERFFEE), high-water mark indicator (HWM), lock-up period in years (LOCKUP), leverage indicator (LEVERAGE), 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. The *t*-statistics, in parentheses, are derived from robust standard errors that are clustered by fund and month. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Independent Variable	Dependent Variable							
	RETURN	ALPHA	RETURN	ALPHA	RETURN	ALPHA	RETURN	ALPHA
	1	2	3	4	5	6	7	8
FWHR	−0.695**	−0.674**			−0.392*	−0.604**		
	(−2.88)	(−2.70)			(−1.98)	(−3.94)		
FWHR_RANK			−0.414**	−0.399**			−0.185	−0.351**
			(−2.93)	(−3.01)			(−1.64)	(−4.16)
MARRIED	−1.217*	−1.509*	−0.239*	−0.219				
	(−2.00)	(−2.05)	(−2.21)	(−1.78)				
MARRIED × FWHR	0.770*	0.943*						
	(2.33)	(2.42)						
MARRIED FWHR_RANK			0.483**	0.498**				
			(2.89)	(2.83)				
FATHER					−1.557	−1.540*	−0.379*	−0.226
					(−1.68)	(−2.27)	(−2.06)	(−1.74)
FATHER × FWHR					0.924	0.838*		
					(1.93)	(2.35)		
FATHER × FWHR_RANK							0.485	0.480*
							(1.95)	(2.50)
Other fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.028	0.019	0.028	0.019	0.031	0.018	0.031	0.018
No. of obs.	43,252	32,921	43,252	32,921	49,444	37,896	49,444	37,896

To further distinguish from the competing explanation based on stereotypes, we next focus on newlyweds and new fathers. Research suggests that men in romantic and committed relationships have lower testosterone and this effect dominates that of marriage (Burnham, Chapman, Gray, McIntyre, Lipson, and Ellison (2003), Marazziti and Canale (2004)). Consequently, newly married men, who are presumably still in a romantic relationship with their partners, should experience the steepest declines in testosterone. Moreover, the effect of fatherhood on testosterone is strongest for fathers with young children (Gettler et al. (2011)). Therefore, we reestimate the Table 9 regressions with NEWLY_MARRIED and NEW_FATHER, indicator variables that take values of 1 for managers who marry within the past year and managers with young children who are less than a year old, respectively. Supplementary Material Table S5 indicates that the results are indeed stronger for such managers.

One concern is that marriage and fatherhood may for reasons unrelated to testosterone affect the relative performance of high- versus low-fWHR fund managers. We consider 2 possible reasons: limited attention and performance persistence. While limited attention may explain the negative coefficient estimates on

MARRIED and FATHER in some specifications à la Lu, Ray, and Teo (2016), it is difficult to explain the positive coefficient estimates on the interaction terms with limited attention since it is not clear why high-fWHR men should be less affected by limited attention than are low-fWHR men. Moreover, we find that marriage and fatherhood ameliorate the underperformance of high-fWHR managers even for managers who have been married for more than 1 year or who have children that are more than a year old, which is hard to reconcile with the limited attention view since the effects of limited attention should be largely confined to the period immediately surrounding a marriage or childbirth. Our results also cannot be explained by the possibility that better-performing high-fWHR managers and poorer performing low-fWHR managers are more likely to marry or father children and that fund performance persists over time. In unreported probit regressions, we find no evidence to suggest that the interaction between past fund performance and fWHR positively relates to the probability of getting married or producing offspring. In results available upon request, we also find that inferences do not change when we control for manager biological age in the Table 9 regressions. Overall, the findings in this section further bolster the circulating testosterone view and provide insights into the biological mechanism underpinning the relation between fWHR and manager behavior.

G. Sample Selection

Sample selection may cloud inferences from our results. The coefficients in Table 3 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 this issue, we follow Ramadorai (2012) and employ the Heckman (1979) 2-stage procedure to correct for possible sample selection bias. Specifically, 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. The exclusion restriction that we employ is firm strategy flow at founding, which is motivated by the Asker, Farre-Mensa, and Ljungqvist (2015) choice of venture capital supply at founding to instrument for firm listing status. Firm strategy flow at founding is the strategy flow of the first fund conceived by the firm in the firm inception year. Managers of funds in firms that engage in popular strategies 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, strategy flow at firm inception significantly explains future fund performance. Indeed, the strategy used to determine firm strategy flow at inception may well differ from the strategies employed by the follow-on funds (i.e., nonfirst funds) launched by the firm, further motivating the exclusion restriction. To further ensure that firm strategy flow at inception 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 firm strategy flow at inception as the independent variable. In line with our intuition, the coefficient estimate on firm strategy flow at inception 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 on the inverse Mills ratio takes the sign of the correlation between the residuals in the regressions that explain selection and hedge fund performance. While the coefficient on the inverse Mills ratio is positive for the regression on monthly returns and negative for the regression on monthly alphas, the coefficients are statistically indistinguishable from 0 at the 10% level in both cases. Therefore, there is no statistically meaningful relation between image availability and unexplained fund performance. Moreover, the estimates from the second

TABLE 10

Heckman Selection Model

The Heckman (1979) selection model is used to control for selection bias in regressions on the cross-section of hedge fund performance. The dependent variables in Table 10 include RETURN and ALPHA where RETURN is the monthly hedge fund net-of-fee return and ALPHA is the Fung and Hsieh (2004) monthly alpha with factor loadings estimated over the last 24 months. The primary independent variable of interest is fund fWHR (FWHR). The other independent variables include fund management fee (MGTFEE), performance fee (PERFFEE), high-water mark indicator (HWM), lock-up period in years (LOCKUP), leverage indicator (LEVERAGE), 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 that the facial image of a hedge fund's manager is available on the Internet. The exclusion restriction we use in the selection equation is the firm strategy flow during the firm inception year (INCEPTION_STRATFLOW). Columns 4 and 5 report the regression results after correcting for selection bias by incorporating the inverse Mills ratio (INVERSE_MILLS_RATIO) computed from the first stage probit. The *t*-statistics, in parentheses, are derived from robust standard errors that are clustered by fund and month. The *z*-statistics are in square brackets. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

			Heckman Model		
	OLS Regression		Selection	Regression Equation	
	RETURN	ALPHA	Equation	RETURN	ALPHA
Independent Variable	(1)	(2)	(3)	(4)	(5)
FWHR	−0.384*	−0.327**		−0.419*	−0.405**
	(−2.34)	(−3.06)		[−2.20]	[−3.32]
MGTFEE	0.100	0.093*		0.121*	0.115**
	(1.83)	(2.11)		[2.15]	[2.63]
PERFFEE	−0.008	0.001		−0.004	0.004
	(−1.92)	(0.38)		[−0.82]	[1.01]
HWM	0.162**	0.153**		0.095	0.024
	(3.49)	(3.85)		[1.46]	[0.41]
LOCKUP	0.062	0.022		0.049	0.015
	(1.56)	(0.60)		[1.19]	[0.33]
LEVERAGE	0.011	0.031		0.026	0.026
	(0.32)	(0.83)		[0.56]	[0.61]
AGE	−0.008**	−0.007**		−0.044**	−0.027*
	(−2.66)	(−2.82)		[−3.01]	[−1.98]
REDEMPTION	0.014*	0.003		0.005	−0.003
	(2.40)	(0.54)		[0.71]	[−0.54]
log(FUNDSIZE)	−0.066**	−0.004		0.015	−0.055**
	(−4.04)	(−0.31)		[0.87]	[−2.85]
INVERSE_MILLS_RATIO				0.657	−0.257
				[1.24]	[−0.40]
INCEPTION_STRATFLOW			0.031**		
			[3.68]		
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.029	0.016	0.016	0.007	0.005
No. of obs.	133,906	102,026	10,044	133,578	99,711

stage regressions reported in columns 4 and 5 of Table 10 indicate that our findings are even stronger after controlling for sample selection.

For robustness, we consider 2 alternative exclusion restrictions: i) strategy flow in the 24-month period prior to firm inception and ii) the logarithm of firm inception AUM. Panels A and B of Table 11 reveal that our results are robust to employing these alternative exclusion restrictions.

IV. Robustness Tests

We present a battery of robustness tests that ascertain the strength of our empirical results.

A. Endogenous Matching

One concern is that endogenous matching may drive differences in the quality of firms that match to managers based on fWHR. To adjust for time-invariant differences in firm quality, we include firm fixed effects in the baseline performance regressions. To cater for other differences in firm quality, we redo the baseline performance regressions on the first funds launched by hedge fund firms. Since firm founders are more likely to manage first funds, endogenous matching concerns are less relevant for such funds. As Panels C and D of Table 11 show, the results are qualitatively unchanged after adjusting for endogenous matching.

B. Manager Age

Yet another concern is that the manager's biological age could explain our results. To account for manager biological age, we cull information on fund manager date of birth from Peoplewise (www.peoplewise.com), which is available for about 47.87% of the managers in our sample.[24] Next, we rerun the baseline regressions for this subsample after controlling for manager age. Panel E of Table 11 indicates that inferences remain unchanged with this adjustment.

C. Sensation Seeking

To control for sensation seeking (Campbell, Dreber, Apicella, Eisenberg, Gray, Little, Garcia, Zamore, and Lum (2010)), we include an additional independent variable based on whether the fund manager purchased a sports car (Brown et al. (2018)). We obtain vehicle information for 955 funds in our sample by searching for new vehicles purchased by hedge fund managers between 2006 and 2012 from vin.place as per Brown et al. (2018). In an alternative test, we include an additional independent variable based on the number of speeding tickets incurred by each manager (Grinblatt and Keloharju (2009)). We download speeding ticket information, including null records, for 1,259 managers by searching court

[24]We find that high- and low-fWHR managers are on average 44.5 and 45.1 years old, respectively. The biological age difference is statistically indistinguishable from zero at the 10% level. While testosterone decreases gradually for 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)).

TABLE 11

Robustness Tests

Table 11 reports results from multivariate OLS regressions on hedge fund performance. The dependent variables include RETURN and ALPHA where RETURN is the monthly hedge fund net-of-fee return and ALPHA is the Fung and Hsieh (2004) monthly alpha with factor loadings estimated over the last 24 months. The primary independent variable of interest is fund fWHR (FWHR). The other independent variables include fund management fee (MGTFEE), performance fee (PERFFEE), high-water mark indicator (HWM), lock-up period in years (LOCKUP), leverage indicator (LEVERAGE), 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. FH denotes the Fung and Hsieh (2004) model. The *t*-statistics, in parentheses, are derived from robust standard errors that are clustered by fund and month. The *z*-statistics are in square brackets. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Independent Variable	Dependent Variable	
	RETURN	ALPHA
	(1)	(2)
Panel A. Strat Flow 24-Month Prior to Firm Inception as Excl. Restriction		
FWHR	−0.407**	−0.367**
	[−2.68]	[−2.79]
Panel B. Logarithm of Firm Inception AUM as Excl. Restriction		
FWHR	−0.514*	−0.386**
	[−2.56]	[−2.71]
Panel C. Controlling for Endogenous Matching via Firm Fixed Effects		
FWHR	−0.336*	−0.279*
	(−2.12)	(−2.34)
Panel D. Controlling for Endogenous Matching via First Funds		
FWHR	−0.364**	−0.298*
	(−3.27)	(−2.51)
Panel E. Controlling for Manager Age		
FWHR	−0.332*	−0.495**
	(−2.10)	(−3.35)
Panel F. Controlling for Sensation Seeking via Sports Car Ownership		
FWHR	−0.585*	−0.659**
	(−2.24)	(−2.64)
Panel G. Controlling for Sensation Seeking via Speeding Tickets		
FWHR	−0.365*	−0.311**
	(−2.33)	(−3.06)
Panel H. Caucasian Fund Managers		
FWHR	−0.382*	−0.322**
	(−2.33)	(−2.99)
Panel I. fWHR Computed Using a Python Algorithm		
FWHR	−0.528*	−0.524**
	(−2.36)	(−2.99)
Panel J. Chief Investment Officers and Portfolio Managers		
FWHR	−0.731**	−0.442**
	(−3.59)	(−2.59)
Panel K. Fund Management Company CEOs		
FWHR	0.515	0.456
	(1.77)	(1.69)
Panel L. Face Width-to-Lower Height Ratio (FWLHR)		
FWLHR	−0.338**	−0.295**
	(−4.27)	(−4.66)

(continued on next page)

TABLE 11 (continued)

Robustness Tests

Independent Variable	Dependent Variable	
	RETURN (3)	ALPHA (4)
Panel M. Face Lower Height-to-Whole Face Height Ratio (LHWH)		
LHWH	0.808** (2.37)	0.616* (2.39)
Panel N. Adjusted for Fund Termination		
FWHR	−0.514** (−3.20)	−0.479** (−4.29)
Panel O. Adjusted for Incubation Bias		
FWHR	−0.441* (−2.54)	−0.338** (−3.08)
Panel P. Adjusted for Backfill Bias		
FWHR	−0.323* (−2.32)	−0.324* (−2.45)
Panel Q. Adjusted for Serial Correlation		
FWHR	−0.542** (−4.56)	−0.534** (−5.29)
Panel R. Prefee Returns		
FWHR	−0.475* (−2.27)	−0.454** (−3.30)
Panel S. FH + An Emerging Markets Factor		
FWHR	−0.397* (−2.45)	−0.309* (−2.28)
Panel T. FH + The Pastor and Stambaugh (2003) Liquidity Factor		
FWHR	−0.398* (−2.46)	−0.522** (−2.65)
Panel U. FH + The Agarwal and Naik (2004) Option Based Factors		
FWHR	−0.398* (−2.46)	−0.493** (−2.90)
Panel V. Returns Computed From 13F Long-Only Holdings		
FWHR	−0.259** (−4.44)	−0.210** (−2.63)
Panel W. Systematic Strategies		
FWHR	−0.267 (−1.41)	−0.319 (−1.47)
Panel X. Discretionary Strategies		
FWHR	−0.486** (−2.85)	−0.459** (−3.91)

records on the PeopleFinders data set using manager name, city, and state. Panels F and G of Table 11 verify that sensation seeking does not drive our findings.

D. Barriers to Entry

Our findings could be driven by the potentially greater barriers to entry that low-fWHR managers face due to erroneous stereotypes of successful managers.

However, we find that the correlation between fund inception AUM and fund fWHR at 0.0165 is economically modest and statistically unreliable, casting doubt on the barriers to entry view. To investigate further, we sort hedge funds based on *fund* strategy flow during fund inception year. We find that the baseline results are even stronger for funds launched during years with above-median strategy flow (i.e., when barriers to entry are likely to be less pertinent). These results cast further doubt on the barriers to entry story.

E. Manager Race

If fWHR varies systematically by manager race, our baseline findings may capture a race fixed effect instead. Since most of our managers are Caucasians (2,432 out of the 2,446 managers), to address this concern, we reestimate the baseline regressions for this group of managers. Panel H of Table 11 indicates that our findings are not driven by manager race.

F. Computing fWHR via Python

To address reproducibility concerns, instead of computing fWHR by hand using the ImageJ software tool, we compute fWHR using the Python algorithm written by Ties de Kok that employs the face_recognition package.[25] Panel I of Table 11 reveals that our findings are robust to fWHR computed using the Python program.

G. Manager Functional Roles

Our results should be stronger for managers who are primarily responsible for the investment activities at their funds. To test, we redo the baseline regressions separately for Chief Investment Officers/Portfolio Managers and for CEOs (who are not also Chief Investment Officers). Manager functional role information is available for 2,231 of the 2,446 managers. Panels J and K of Table 11 indicate that the negative relation between fWHR and fund performance is indeed driven by Chief Investment Officers/Portfolio Managers and not by CEOs. The positive relation between fWHR and investment performance for CEOs is consistent with Wong, Ormiston, and Haselhuhn's (2011) conclusion that fWHR is helpful for executive leadership.

H. Alternative Biomarkers for Testosterone

To further test the testosterone view, we compute face width-to-lower face height (fWLHR) and lower face height-to-whole face height (LHWH) and reestimate the baseline regressions with fWLHR or LHWH in place of fWHR. Lefevre et al. (2013) report that fWLHR is positively related and LHWH is negatively related to circulating testosterone for men. 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

[25]Please see https://github.com/TiesdeKok/fWHR_calculator/blob/master/FWHR_calculator.ipynb for more information on the Python algorithm.

chin (see their Table 2). The advantage of using LHWH as a proxy for testosterone is that it is less affected by facial adiposity concerns since the calculation of LHWH does not involve facial width. Panels L and M of Table 11 suggest that our findings are qualitatively unchanged with these alternative biomarkers for testosterone.

I. Fund Termination

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

J. Incubation Bias

Hedge fund firms often incubate new funds with internal capital. These funds are subsequently marketed to outside investors conditional on establishing a track record, which could lead to an incubation bias (Fung and Hsieh (2009)). To ameliorate incubation bias, we remove the first 24 months of returns for each fund and reestimate the baseline regressions. Panel O of Table 11 indicates that the findings are not driven by incubation bias.

K. Backfill Bias

To address backfill bias concerns (Fung and Hsieh (2009), Bhardwaj, Gorton, and Rouwenhorst (2014)), we rerun the baseline performance regressions after dropping returns reported prior to database listing. Both HFR and TASS report listing dates.[26] For funds that report to other databases, we employ the Jorion and Schwarz (2019) algorithm to back out listing dates. Panel P of Table 11 reveals that our findings are not driven by backfill bias.

L. Serial Correlation in Fund Returns

Serial correlation in fund returns 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). Panel Q of Table 11 indicates that our conclusions are unchanged after adjusting for return serial correlation.

M. Fund Fees

To derive pre-fee returns, we match each capital outflow to the relevant capital inflow when calculating the high-water mark and the performance fee by assuming as per Appendix A of Agarwal, Daniel, and Naik (2009) that capital leaves the fund

[26]Jorion and Schwarz (2019) observe that TASS does not report listing dates post Mar. 2011. They use the Feb. 2019 snapshot of TASS. We download TASS listing dates from the July 2019 snapshot of TASS. For that version of TASS, we are able to find listing dates that are dated post Mar. 2011. It appears that TASS has fixed the problem with listing dates.

on a first-in, first-out basis. Panel R of Table 11 shows that our findings apply to gross returns.

N. Omitted Risk Factors

To ameliorate concerns stemming from omitted risk factors, we separately augment the Fung and Hsieh (2004) model with the excess return from the MSCI Emerging Markets Index, the Pástor and Stambaugh (2003) liquidity factor, and the Agarwal and Naik (2004) out-of-the-money S&P 500 call and put option-based factors. Panels S–U of Table 11 indicate that our baseline results are not driven by omitted risk factors.

O. Fund Performance Manipulation

To address concerns stemming from fund manager manipulation of reported returns, we rerun our baseline regressions with returns computed from Thomson Financial 13F long-only filings that are reported to the SEC and are, therefore, more costly to manipulate. Panel V of Table 11 reveals that our findings are not driven by fund manager manipulation.

P. Systematic Versus Discretionary Strategies

If the results are driven by manager testosterone, they should be stronger for nonsystematic hedge funds who exercise greater discretion when executing their investment strategies. To test, we split the sample into systematic versus discretionary funds using the algorithm of Harvey, Rattray, Sinclair, and van Hemert (2017). About 15% of the sample are systematic funds. Panels W and X of Table 11 indicate that the findings are indeed stronger for discretionary funds.

V. Out-of-Sample Test: Mutual Funds

As an out-of-sample test and to investigate whether our findings extend beyond the hedge fund arena, we redo our fund performance analysis on actively managed U.S. equity mutual funds using data from the CRSP survivorship-free mutual fund database. During our sample period, there are 25,849 actively managed equity mutual funds in the CRSP sample. We drop mutual funds that are managed by anonymous teams or that report manager last names only. This leaves us with 12,322 funds. As per the hedge fund sample, we search for manager photos from the Internet and focus on male managers with forward facing photos and without significant facial adiposity. All in all, we are able to obtain valid fund manager photos for 5,740 mutual funds.[27]

First, we sort mutual funds into 10 portfolios based on fund fWHR every Jan. 1st. We then evaluate the post-formation returns on these 10 portfolios relative to the Carhart (1997) 4-factor model. Panel A of Table 12 indicates that high-fWHR

[27]An advantage of analyzing mutual funds is that since mutual fund manager photos are readily available from the Internet, our analysis is less affected by sample selection issues. As discussed, a disadvantage is that endogenous matching between fund managers and mutual fund firms may cloud inferences from the results.

mutual funds underperform low-fWHR mutual funds by a substantive 9.03% per year (t-stat = 19.03). After adjusting for risk, the underperformance reduces slightly to 8.79% per year (t-stat = 20.89). The reduction is driven by the negative loading on RMRF and SMB for the spread portfolio. During the sample period, the market risk premium was positive and small stocks outperformed large stocks. We note that the average fWHR for the high-fWHR funds in Portfolio 1 is 2.19 and that for the low-fWHR funds in Portfolio 10 is 1.52.

The greater underperformance of high- versus low-fWHR mutual funds (Panel A, Table 12) relative to high- versus low-fWHR hedge funds (Panel A, Table 2) is consistent with the self-selection biases inherent in hedge fund data (Fung and Hsieh (2009)). For example, high-fWHR hedge funds, which are more likely to underperform, could stop reporting returns prematurely as they may no longer be able to attract new capital given their underperformance while low-fWHR hedge funds, which are more likely to outperform, could stop reporting returns prematurely as they may be closed to new investments. Such self-selection biases, which are absent in mutual fund data, could therefore curb the number of return observations associated with extreme-fWHR hedge funds.[28]

Next, we estimate the following OLS multivariate regression on mutual fund performance:

$$\begin{aligned}(2)\qquad \text{ALPHA}_{im} = {} & \alpha + \beta_1 \text{FWHR}_i + \beta_2 \text{EXPENSE}_i + \beta_3 \text{LOAD}_i + \beta_4 \text{AGE}_{im-1} \\ & + \beta_5 \log\left(\text{TNA}_{im-1}\right) + \sum_k \beta_6^k \text{STRATEGYDUM}_i^k \\ & + \sum_k \beta_7^k \text{YEARDUM}_m^l + \epsilon_{im},\end{aligned}$$

where ALPHA is fund alpha, FWHR is fund fWHR, EXPENSE is fund expense ratio, LOAD is maximum load or the sum of maximum front-end, back-end, and deferred sales charges, AGE is fund age, and TNA is fund total net assets. Fund alpha is monthly abnormal return from the Carhart (1997) model, where the factor loadings are estimated over the prior 24 months. We also estimate the analogous regression on monthly fund excess returns as well as regressions with FWHR_RANK in place of FWHR. Statistical inferences are based on White (1980) robust standard errors clustered by fund and month.

Panel B of Table 12 corroborates the portfolio sorts. The coefficient estimate on ALPHA in column 2 indicates that high-fWHR mutual funds underperform low-fWHR mutual funds by a risk-adjusted 1.65% per year (t-stat = 3.55) after accounting for various mutual fund characteristics. Column 1 suggests that our results apply to raw mutual fund returns, while columns 3 and 4 reveal that our findings are robust

[28]It is worth noting that the alpha of the low-fWHR mutual fund portfolio is positive and economically significant at 4.69% per annum (t-stat = 6.57). This is somewhat surprising in light of the absence of self-selection biases in the mutual data and the results of Carhart ((1997), Table III). One possibility is that low-fWHR fund managers, by investing prudently and avoiding the mistakes that high-fWHR fund managers make, namely, trading too actively, preferring lottery-like stocks, and succumbing to the disposition effect, are able to outperform not only on a relative basis (i.e., relative to other funds) but also on an absolute basis.

TABLE 12

Tests of Mutual Fund Performance

Panel A of Table 12 reports results from portfolio sorts on mutual fund facial width-to-height ratio (fWHR). Portfolio performance is estimated relative to Carhart (1997) 4 factors: RMRF, SMB, HML, and UMD. RMRF is the excess return on Fama and French's (1993) market proxy. SMB, HML, and UMD are Fama and French's factor mimicking portfolios for size, book-to-market equity, and 1-year return momentum. The *t*-statistics are derived from White (1980) standard errors. Panel B reports results from multivariate regressions on mutual fund performance. The dependent variables include RETURN and ALPHA, where RETURN is the monthly mutual fund net-of-fee return and ALPHA is the Carhart (1997) monthly alpha with factor loadings estimated over the last 24 months. The primary independent variables of interest are fund fWHR (FWHR) and fWHR percentile rank (FWHR_RANK) which is computed every year and takes values from 0 to 1. The other independent variables include mutual fund expense ratio (EXPENSE), maximum load (LOAD), age in years (AGE), and log of total net assets (log (TNA)) as well as dummy variables for year and fund investment strategy. The *t*-statistics, in parentheses, are derived from robust standard errors clustered by fund and month for the OLS regressions and derived from Newey and West (1987) standard errors with a 3-month lag for the Fama and MacBeth (1973) regressions. The sample period is from Jan. 1994 to Dec. 2015. * and ** denote significance at the 5% and 1% levels, respectively.

Panel A. Portfolio Sorts on Mutual Fund fWHR

Mutual Fund Portfolio	Excess Return (Annualized) 1	*t*-Statistic of Excess Return 2	Alpha (Annualized) 3	*t*-Statistic of Alpha 4	RMRF 5	SMB 6	HML 7	UMD 8	Adj. R^2 9
Portfolio 1 (high fWHR)	1.59	0.50	−4.10**	−5.47	0.91**	0.33**	−0.03	0.02	0.949
Portfolio 2	6.13	1.82	0.02	0.04	0.97**	0.38**	0.00	0.00	0.964
Portfolio 3	6.10	1.94	0.42	0.55	0.92**	0.27**	0.04	0.00	0.946
Portfolio 4	5.93	1.85	0.16	0.26	0.94**	0.29**	0.03	−0.01	0.965
Portfolio 5	6.11	1.86	0.20	0.31	0.95**	0.34**	0.01	0.00	0.960
Portfolio 6	5.69	1.76	−0.01	−0.01	0.95**	0.29**	0.00	−0.01	0.966
Portfolio 7	6.36*	1.96	0.44	0.70	0.95**	0.33**	0.01	0.00	0.966
Portfolio 8	5.63	1.72	−0.13	−0.20	0.94**	0.36**	0.02	−0.02	0.963
Portfolio 9	6.02	1.80	0.08	0.11	0.97**	0.32**	−0.03	0.00	0.957
Portfolio 10 (low fWHR)	10.62**	3.17	4.69**	6.57	0.96**	0.37**	−0.05	0.00	0.957
Spread (1–10)	−9.03**	−19.03	−8.80**	−20.89	−0.06**	−0.04**	0.01	0.01	0.221

Panel B. Multivariate Regressions on Mutual Fund Performance

	OLS Regressions				Fama–MacBeth Regressions			
	RETURN	ALPHA	RETURN	ALPHA	RETURN	ALPHA	RETURN	ALPHA
Independent Variable	1	2	3	4	5	6	7	8
FWHR	−0.193**	−0.206**			−0.189**	−0.186**		
	(−2.75)	(−3.55)			(−5.06)	(−5.75)		
FWHR_RANK			−0.063**	−0.040*			−0.064**	−0.065**
			(−6.39)	(−2.49)			(−2.69)	(−2.86)
EXPENSE	−9.282**	−7.549**	−9.119**	−7.759**	−8.453**	−7.045**	−8.946**	−7.428**
	(−3.27)	(−3.00)	(−3.20)	(−3.17)	(−4.30)	(−5.70)	(−4.56)	(−6.03)
LOAD	0.002	0.002	0.002	0.003	−0.481*	−0.063	−0.412	−0.008
	(0.65)	(0.89)	(0.81)	(1.16)	(−2.15)	(−0.57)	(−1.88)	(−0.07)
log(TNA)	−0.000*	0.000	−0.000*	0.000	−0.000	0.000	−0.000	0.000
	(−2.53)	(1.36)	(−2.50)	(1.51)	(−0.79)	(0.62)	(−0.66)	(0.81)
AGE	0.005	−0.000	0.005	−0.000	−0.001	−0.000	−0.001	−0.000
	(1.10)	(−0.00)	(1.13)	(−0.39)	(−0.64)	(−0.52)	(−0.71)	(−0.59)
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
R^2	0.070	0.025	0.070	0.024	0.375	0.349	0.376	0.350
No. of obs.	247,419	218,866	247,419	218,866	247,419	218,866	247,419	218,866

when we analyze fWHR rank. We also estimate Fama and MacBeth (1973) regressions on mutual fund performance and report qualitatively similar results in columns 5–8. Results, available from the authors, indicate that the findings remain qualitatively unchanged when we i) study style-adjusted performance, ii) analyze pre-fee returns, or iii) evaluate performance using the Fama and French (2016) 5-factor model.

VI. Conclusion

This article investigates the link between fWHR and investment performance for a large sample of hedge fund managers. By doing so, this study makes several contributions to the finance literature.

First, we present novel results on the relation between fWHR and investment performance. The findings on the underperformance of high-fWHR hedge fund managers, relative to low-fWHR hedge fund managers, offer fresh insights relative to prior studies on intraday traders. Our identification strategy, which exploits major personal events such as marriage and fatherhood that shape testosterone levels in men, allows us to address endogeneity concerns and trace the biological mechanism underlying the negative relation between fWHR and investment performance to circulating testosterone. By doing so, we overcome the shortcoming of this line of research whereby the association between fWHR and testosterone is typically assumed but not assessed. Second, we find that high-fWHR hedge fund managers exhibit greater operational risk and bear more left tail risk. They are more likely to fail even after controlling for past performance, disclose more regulatory, civil, and criminal violations, exhibit higher downside betas, and experience larger drawdowns. Third, we show that facial width can underlie behavioral biases such as the disposition effect and the preference for lotteries. These behavioral biases in turn engender poorer investment performance. Fourth, we document that hedge fund manager facial width is associated with a greater asset-liability mismatch, which translates into asset fire sales and purchases when investors redeem from and subscribe to funds, respectively. Fifth, we find that by promoting their funds more aggressively, high-fWHR hedge fund managers garner more flows and harvest greater fee revenues. These results rationalize why high-fWHR hedge fund managers can survive despite underperforming their competitors. Sixth, we show that the negative relation between fWHR and investment performance extends to actively managed equity mutual funds, which suggests that our findings apply broadly to delegated portfolio management.

These results are relevant for investment fiduciaries such as university endowments, pension funds, and sovereign wealth funds that allocate capital to hedge funds and other portfolio managers. While some investors may be tempted, based on our findings, to discriminate among fund managers based on facial width, we believe that it is more constructive for investors to select managers based on their assessment of the fund managers' personality traits associated with facial width (e.g., aggression), since it is ultimately those managerial traits that impact fund performance and investment behavior.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109021000399.

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