

# THREE ESSAYS ON HEDGE FUNDS

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by

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Three Essays on Hedge Funds

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Le doyen  
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# Abstract

This dissertation empirically analyzes risk, return, and flow determinants of hedge funds. It consists of three essays, the second and third of which are written in consultation with Professors Vikas Agarwal, Stefan Ruenzi, and Florian Weigert.

The first essay uses novel data on net leverage to more accurately measure the market beta of long/short equity hedge funds. Net leverage, and thus market beta, is found to be procyclical. At fund inception, managers set net-leverage targets based on recent market performance to attract investors. Post-inception, managers allow net leverage to fluctuate with (1) investor flows and (2) changes in the mark-to-market value of the fund portfolio. These fluctuations explain the previously documented exposure of long/short equity hedge fund returns to the time-series momentum of equity indices.

The second essay combines historical versions of hedge fund databases with Form ADV filings to derive new insights into fund manager careers and incentive structures within hedge fund firms. Managerial firm control (*CONTROL*) and equity ownership (*STAKE*) are prevalent, consistent with hedge fund managers being entrepreneurs rather than employees. Holding *STAKE* or exercising *CONTROL* lowers the likelihood of a manager leaving a fund. The underperformance of team-managed versus solo-managed hedge funds is not robust to controlling for potential conflicts arising from team members' *STAKE*. Both US-domiciled hedge funds and hedge funds with high *SKIN* exhibit a weaker flow-performance relation. A U-shaped relationship exists between *SKIN* and fund age. Finally, hedge fund asset returns cannot be directly inferred from gross leverage and fund returns.

In hedge funds, the main contact person (CP) responsible for investor relations is often different from the person making the investment decisions. The third essay shows that hedge funds with female CPs grow their assets under management faster, by 2% annually, than those with male CPs. This bias is not explained by the fact that female CPs more often than male CPs occupy marketing-focused positions. Instead, flows from funds of hedge funds suggest that male investors gravitate towards hedge funds with female CPs. Women also demonstrate greater career mobility, strategically choosing to work for funds that have recently performed well.

**Keywords:** Hedge funds, Leverage, Long/short equity, Fund manager changes, Investor relations

**JEL:** G11, G23, G32, M31

# Résumé

Cette thèse analyse empiriquement les déterminants du risque, du rendement et des flux en matière de fonds spéculatifs. Elle se compose de trois essais, dont le deuxième et le troisième ont été rédigés en consultation avec les professeurs Vikas Agarwal, Stefan Ruenzi et Florian Weigert.

Le premier essai utilise de nouvelles données sur l'effet de levier net pour mesurer plus précisément le bêta du marché pour les fonds spéculatifs d'actions longues/courtes. L'effet de levier net, et donc le bêta du marché, s'avère procyclique. Au lancement du fonds, les gestionnaires fixent des objectifs d'endettement net en fonction des performances récentes du marché pour attirer les investisseurs. Après la création, les gestionnaires permettent à l'effet de levier net de fluctuer avec (1) les flux d'investisseurs et (2) les variations dans la valeur de marché du portefeuille du fonds. Ces fluctuations expliquent l'exposition précédemment documentée des rendements des fonds spéculatifs d'actions longues/courtes à l'élan des séries chronologiques des indices d'actions.

Le deuxième essai combine des versions historiques de bases de données de fonds spéculatifs avec des dépôts de formulaire ADV pour en tirer de nouvelles perspectives sur les carrières de gestionnaire de fonds et les structures d'incitation au sein des sociétés de fonds spéculatifs. Le contrôle de l'entreprise (*CONTROL*) et la participation au capital (*STAKE*) sont prévalents, ce qui correspond au fait que les gestionnaires de fonds spéculatifs sont des entrepreneurs plutôt que des employés. Détenir un *STAKE* ou exercer un *CONTROL* réduit la probabilité qu'un gestionnaire quitte un fonds. La sous-performance des fonds spéculatifs gérés en équipe par rapport à ceux gérés en solo n'est pas suffisante pour contrôler les conflits potentiels découlant du *STAKE* des membres de l'équipe. Les fonds spéculatifs domiciliés aux États-Unis et les fonds spéculatifs à *SKIN* élevé présentent un rapport flux-performance plus faible. Il existe une relation en forme de U entre *SKIN* et l'âge du fonds. Enfin, les rendements des actifs des fonds spéculatifs ne peuvent pas être directement déduits de l'effet de levier brut et des rendements des fonds.

Dans les fonds spéculatifs, l'interlocuteur principal (IP) responsable des relations avec les investisseurs est souvent différente de la personne qui prend les décisions d'investissement. Le troisième essai montre que les fonds spéculatifs avec des IP féminins augmentent leurs actifs sous gestion plus rapidement, de 2% par an, que ceux avec des IP masculins. Ce biais ne s'explique pas par le fait que les IP féminins occupent plus souvent que les IP masculins des postes axés sur le marketing. Au lieu de cela, les flux des fonds de fonds spéculatifs suggèrent que les investisseurs masculins gravitent vers les fonds spéculatifs avec des IP féminins. Les femmes font également preuve d'une plus grande mobilité professionnelle, choisissant stratégiquement de travailler pour des fonds qui ont récemment obtenu de bons résultats.

**Mots clés:** Fonds spéculatifs, Effet de levier, Actions longues/courtes, Changements de gestionnaire de fonds, Relations avec les investisseurs

**JEL:** G11, G23, G32, M31



# Contents

<b>Acknowledgments</b>	<b>v</b>
<b>Abstract</b>	<b>vi</b>
<b>Résumé</b>	<b>vii</b>
<b>Contents</b>	<b>ix</b>
<b>List of Figures</b>	<b>xiii</b>
<b>List of Tables</b>	<b>xv</b>
<b>General Introduction</b>	<b>1</b>
<b>1 The Long and Short Leverage of Long/Short Equity Hedge Funds</b>	<b>9</b>
1.1 Introduction . . . . .	9
1.2 Data . . . . .	10
1.2.1 Data sources . . . . .	11
1.2.2 Summary statistics . . . . .	12
1.2.3 Leverage levels over time . . . . .	12
1.3 Net leverage as a measure of market beta . . . . .	13
1.3.1 Long- and short-book betas . . . . .	14
1.3.2 Forecasting power of net leverage . . . . .	15
1.4 Net-leverage changes are relevant . . . . .	16
1.5 Net leverage is subject to “drifts” . . . . .	17
1.5.1 Intuition . . . . .	17
1.5.2 Calculation of leverage drifts . . . . .	18
1.5.3 Regression model . . . . .	19
1.5.4 Regression results . . . . .	19
1.5.5 Further robustness tests . . . . .	22
1.6 Drifts cause exposure to time-series momentum . . . . .	23

1.7	Net-leverage targets are chosen strategically . . . . .	24
1.8	Conclusion . . . . .	26
	Bibliography . . . . .	28
	Figures . . . . .	33
	Tables . . . . .	35
<b>2</b>	<b>Managerial Changes and Incentive Evolution in Hedge Funds</b>	<b>49</b>
2.1	Introduction . . . . .	49
2.2	Data . . . . .	53
2.2.1	Sample overview . . . . .	53
2.2.2	Preparation of Form ADV data . . . . .	53
2.2.3	Construction of Sample #1 . . . . .	55
2.2.4	Construction of Sample #2 . . . . .	56
2.2.5	Variable construction . . . . .	56
2.3	Descriptive statistics . . . . .	58
2.4	Causes and consequences of managerial turnover . . . . .	58
2.4.1	Event identification . . . . .	58
2.4.2	Causes . . . . .	61
2.4.3	Consequences for fund survival . . . . .	63
2.5	<i>STAKE</i> and performance: why do teams underperform? . . . . .	65
2.6	<i>SKIN</i> , domicile, and the flow-performance relationship . . . . .	67
2.7	<i>SKIN</i> during the hedge fund life cycle . . . . .	71
2.8	Hedge fund leverage and risk . . . . .	73
2.9	Conclusion . . . . .	75
	Bibliography . . . . .	77
	Figures . . . . .	83
	Tables . . . . .	92
2.A	Appendix . . . . .	109
2.A.1	Excerpts from the Form ADV glossary . . . . .	109
<b>3</b>	<b>The (In)visible Women in the Hedge Fund Industry</b>	<b>111</b>
3.1	Introduction . . . . .	111
3.2	Data . . . . .	114
3.2.1	Sample construction . . . . .	114
3.2.2	Determining employee tenure, gender, age, and job role . . . . .	114
3.2.3	Hedge fund returns and AUM . . . . .	116
3.2.4	Variable construction . . . . .	116

---

3.3	Descriptive statistics . . . . .	117
3.4	Male versus female contact persons . . . . .	118
3.4.1	Flows into hedge funds with male versus female contact persons . . . . .	118
3.4.2	Endogeneity . . . . .	119
3.5	Underlying causes . . . . .	120
3.5.1	Job story . . . . .	120
3.5.2	Due diligence story . . . . .	121
3.5.3	Career mobility story . . . . .	122
3.5.4	Attraction story . . . . .	123
3.6	Conclusion . . . . .	125
	Bibliography . . . . .	126
	Figures . . . . .	130
	Tables . . . . .	132
3.A	Appendix . . . . .	145
3.A.1	Identification of hedge fund marketers . . . . .	145
3.A.2	Replicable results . . . . .	146



# List of Figures

1.1	Leverage levels of long/short equity hedge funds . . . . .	33
1.2	Net leverage versus OLS-estimated betas of long/short equity hedge funds . . . . .	34
2.1	Master-fund aggregation in Form ADV data . . . . .	83
2.2	Distribution of <i>TSTAKE</i> and <i>SKIN</i> . . . . .	84
2.3	Data quality: comparison of turnover event dates from different sources . . . . .	85
2.4	Survival times of hedge funds post managerial turnover . . . . .	86
2.5	Number of hedge fund managers versus equity ownership concentration . . . . .	87
2.6	Volatility of monthly hedge fund flows by fund redemption frequency . . . . .	88
2.7	<i>SKIN</i> during the hedge fund life cycle . . . . .	89
2.8	Hedge fund leverage versus fund risk . . . . .	90
3.1	Gender distribution of hedge fund employees across job groups . . . . .	130
3.2	Backfill bias: TASS addition dates versus first appearance in snapshots . . . . .	131



# List of Tables

1.1	Summary statistics . . . . .	35
1.2	Determinants of fund return . . . . .	38
1.3	Tactical versus passive market exposure . . . . .	39
1.4	Economic relevance of net-leverage changes . . . . .	40
1.5	Descriptive statistics of leverage determinants . . . . .	41
1.6	Determinants of net-leverage changes . . . . .	44
1.7	Determinants of net-leverage changes – robustness tests . . . . .	46
1.8	Exposure to leverage drifts ( <i>DRIFT</i> ) and time-series momentum ( <i>TSMOM</i> ) . . . . .	47
1.9	Determinants of net-leverage mandates . . . . .	48
2.1	Availability of database snapshots . . . . .	92
2.2	Summary statistics of Sample #1 . . . . .	93
2.3	Firm ownership ( <i>STAKE</i> ) and control ( <i>CONTROL</i> ) among demographic groups . . . . .	95
2.4	Patterns of manager changes . . . . .	96
2.5	Determinants of portfolio-manager changes . . . . .	97
2.6	Fund survival after manager events . . . . .	100
2.7	Effect of <i>STAKE</i> and team size on performance . . . . .	103
2.8	Effect of <i>SKIN</i> and fund domicile on the flow-performance relationship . . . . .	106
2.9	<i>SKIN</i> during the hedge fund life cycle . . . . .	108
3.1	Availability of historical TASS versions . . . . .	132
3.2	Gender distribution of hedge fund employees by job title . . . . .	133
3.3	Summary statistics . . . . .	134
3.4	Regressions on hedge fund flows . . . . .	137
3.5	Event study around changes in contact person gender . . . . .	138
3.6	“Job story”: regressions on hedge fund flows . . . . .	139
3.7	“Due diligence story”: regressions on hedge fund performance and aggregate flows . . . . .	140
3.8	“Career mobility story”: determinants of contact person turnover . . . . .	141

3.9 “Attraction story”: influence of gender dynamics on hedge fund flows . . . . . 144

# General Introduction

Why do we conduct empirical academic research on hedge funds? The primary reason is that hedge funds are relevant to society and financial markets. Entrusted with trillions of dollars from pension funds, sovereign wealth funds, insurance companies, and university endowments, hedge funds ultimately affect pensioners, taxpayers, students, and other stakeholders. Hedge funds further have a disproportionate impact on market prices and market efficiency as they amplify their influence through leverage, active trading, short selling, and investor engagement (Ben-David et al., 2013; Brunnermeier & Nagel, 2004; Cao et al., 2018; Kokkonen & Suominen, 2015). Finally, hedge fund research offers external validity: hedge funds can serve as a lens through which broader financial phenomena are studied.

However, hedge fund research is limited by the data available. Academics rely on commercial hedge fund databases, which are riddled with biases (Ackermann et al., 1999; Fung & Hsieh, 2000), manipulated (Aragon & Nanda, 2017; Bollen & Pool, 2009), and incomplete (Barth et al., 2023; Brown et al., 2024; Fung & Hsieh, 2009). As a result, many research questions are better answered through studies of investment vehicles with more reliable data, in particular mutual funds. This dissertation acknowledges these limitations in its data selection and choice of research questions. Each chapter uses a novel dataset and investigates aspects unique to hedge funds. Chapter 1 uses a hand-collected dataset on the leverage levels of hedge funds. It addresses the understudied question of how hedge funds determine the degree to which they are invested, long and short, in the market. Chapters 2 and 3 combine historical versions of hedge fund databases to construct time-series information on otherwise static variables. Chapter 2 examines management and incentive structures in hedge funds. Chapter 3 analyzes hedge fund flows to study investor behavior, offering insights into marketing and investor psychology.

Chapter 1 focuses on hedge funds employing the long/short equity strategy. While only a small fraction of mutual funds engage in long-short strategies of any kind,<sup>1</sup> long/short equity (“L/S equity”) has always been the most popular hedge fund strategy. The strategy entails the purchase (long buying) of equity securities that the hedge fund manager perceives as undervalued combined with the simultaneous short selling of equity securities perceived as overvalued. Previous research found that the largest single source of risk for these L/S equity hedge funds is their residual exposure to the equity market. This exposure exists because the (delta-adjusted) market value of securities held long usually exceeds the (delta-adjusted) market value of securities sold short. When analyzing or controlling for this important source of fund risk, the challenge lies in assessing the risk exposure in real time. Researchers calculate the exposure typically as the beta in a regression of fund returns on market-factor returns. If this beta were constant over time, then the intercept – Jensen’s alpha – would measure security-selection ability or market-timing ability (Fama, 1972; Jensen, 1968). However, since hedge fund risk exposures are dynamic (Bollen & Whaley,

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<sup>1</sup>For example, the sample of Badrinath and Gubellini (2011) comprises 110 mutual funds that engage in short selling. Agarwal et al. (2009) compile a sample of 52 “hedged mutual funds”, which are mutual funds mimicking hedge fund strategies.

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2009; Patton & Ramadorai, 2013), alpha measures neither (Chen & Liang, 2007; Jensen, 1972). The issue of non-constant risk exposures is exacerbated by the fact that beta-estimation windows usually need to span at least a year, because hedge fund net asset values (NAVs), from which returns are calculated, are generally determined by the fund administrator at only monthly frequency.<sup>2</sup>

To overcome this challenge, I collect novel data on hedge fund leverage through tedious manual data collection from over 100,000 documents provided by hedge fund firms. The resulting dataset spans 23 years and comprises over 50,000 leverage observations for 432 L/S equity hedge funds. The magnitude, monthly frequency, and strategy-focused nature of the data allow for innovative studies on short-term leverage and risk determinants. For the L/S equity strategy, leverage levels have straightforward implications for risk exposures. Specifically, I demonstrate that the net leverage of a L/S equity hedge fund – its long minus its short leverage – is a more accurate measure of its market-risk exposure than estimated betas. The main findings of Chapter 1 are twofold. First, fund managers allow net leverage to fluctuate in response to two largely external factors: flows of investor capital and changes in the market prices of securities held in the portfolio. Net leverage changes as investors contribute or redeem capital, and as portfolio securities are marked to market. These non-discretionary leverage “drifts” provide a link between the low turnover of L/S equity hedge fund portfolios (Brunnermeier & Nagel, 2004; Griffin & Xu, 2009) and the procyclicality of L/S equity market-risk exposure (Fung & Hsieh, 2004, 2011). The drifts also offer an explanation for the exposure, documented most recently by Ardia et al. (2024), of L/S equity returns to the Moskowitz et al. (2012) time-series momentum of equity indices. Second, the procyclicality of net leverage is further amplified by the fact that fund managers’ choice of net-leverage mandate at fund inception is positively associated with recent market performance: When markets have recently performed well, managers on average choose a more aggressive mandate, and thus a higher market exposure. Consistent with the hypothesis that this behavior is motivated by investor preferences, I observe that, compared to “low-net” L/S equity hedge funds, those with a “high-net” mandate raise more capital at inception after periods of better market returns.

Chapter 2 combines historical versions of hedge fund databases with Form ADV filings to derive new information on fund manager careers and incentive structures within hedge fund firms. Our data confirms that most hedge fund managers are “entrepreneurs” rather than “employees”: 65% hold an equity stake, and 62% are in a position of control at least once during their tenure at a firm. The chapter comprises five analyses, which focus on phenomena that are particular to hedge funds. We first study causes and consequences of manager turnover at hedge funds. Consistent with the stylized fact that most managers are entrepreneurs exempt from termination risk, we find no evidence that departures are preceded by underperformance. This is in contrast to the mutual fund industry, where manager replacements are used as an “internal governance” device (Dangl et al., 2006). Our findings align with theories of managerial entrenchment and career concerns. Second, the hedge fund industry offers a setting to study the interplay of equity ownership and teamwork on performance, as it includes both solo- and team-managed funds, managers with and without equity, and observable performance outcomes in the form of fund returns. Connecting Chen et al. (2024) and Gupta and Sachdeva (2022), we find evidence to attribute the underperformance of team-managed hedge funds to conflicts arising from dispersed equity

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<sup>2</sup>An interesting area of research focuses on the fraction of hedge funds with daily NAV calculation. Kolokolova and Mattes (2018) examine hedge funds that report daily NAVs to Bloomberg, allowing them to observe fund risk, measured as the standard deviation of daily fund returns, on a monthly basis. Such liquid hedge funds may differ from traditional hedge funds. For example, one-third of the hedge funds in the Kolokolova and Mattes (2018) sample are subject to comprehensive regulatory restrictions as they comply with the EU’s UCITS directive (Joenväärä & Kosowski, 2021).

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ownership.

Third, beyond aligning incentives, insider ownership (“skin-in-the-game”) is so substantial in hedge funds – unlike in mutual funds – that it may improve capital stability. Gupta and Sachdeva (2022) find that insider ownership indeed weakens the flow-performance relation in hedge funds. Yet, insiders at hedge fund firms are often US citizens who, for tax purposes, prefer to invest in US-domiciled (“onshore”) funds. Thus, the findings of Gupta and Sachdeva (2022) could be related to those of Aragon et al. (2014), who observe a weaker flow-performance relation for onshore compared to offshore hedge funds. Connecting these two studies, we show that the results of both are robust, and additional tests support the underlying mechanisms proposed in these studies. Fourth, given its relevance for the flow-performance relation, we examine how insider ownership evolves over a hedge fund’s life cycle. We document a U-shaped relationship between insider ownership and fund age; after an estimated 6.34 years following fund launch, the growth of internal capital outpaces that of external capital. Changes in insider ownership are more positive when fund fees are higher, which is consistent with the notion that fees increase insider wealth and widen the gap between the returns on insider versus outsider capital. Finally, using leverage data derived from Gross Asset Values (GAV) included in Form ADV filings, we explore how hedge funds’ use of leverage influences the relationship between their fund returns and asset returns. We caution against a recently proposed methodology that infers asset returns directly from gross leverage and fund returns.

Chapter 3 uses the hedge fund industry as a laboratory to study consumer decision-making. The fund investors are interpreted as consumers, whose capital flows represent decisions to buy and sell products. The laboratory is “clean” in the sense that hedge funds, the “products” in this context, are relatively homogeneous, and their characteristics readily observable. From a marketing perspective, hedge funds operate in a “high-touch” and “high-value” market. The primarily targeted clients are institutional investors, who commit large amounts but also have high investment thresholds. Not only the customers but also the products are demanding: hedge funds are opaque, complex, illiquid, and expensive. As a result, the hedge fund distribution process is both lengthy and personalized. This naturally elevates the importance of the fund’s investor contact person (CP) and her ability to establish personal relationships with individual investors (Gennaioli et al., 2015; Goyal et al., 2023).<sup>3</sup> In contrast, mutual funds are sold in an impersonal manner to a large audience of retail investors. To reach this broad audience, they incur substantial marketing expenses and operate under stricter regulations concerning trading, leverage, disclosure, liquidity, and transparency (Agarwal et al., 2009; Roussanov et al., 2021).

We hypothesize that the hedge fund distribution process exposes investors to emotional biases stemming from personal attributes of the CP. Investors’ objectivity is challenged not only by extensive personal interactions with the CP, but also by the need to make subjective assessments of intangible qualities such as character, trustworthiness, and experience of the hedge fund staff. To investigate, we test whether investors are influenced by the CP’s gender. We focus on gender because it is a readily observable, strong proxy for sex, which shapes multiple personal attributes. The chapter documents an investor preference for hedge funds with female CPs, which experience 2% higher average annual flows compared to those with male CPs. Incorporating information from job titles, we find that this bias is not explained by the fact that women more often than men occupy positions focused on marketing. In fact, when we narrow

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<sup>3</sup>According to the “2023 Investment Company Institute (ICI) Fact Book” (Figure 3.2, p. 3), at year-end 2022, 88% of US mutual fund assets were held by households (<https://www.ici.org/system/files/2023-05/2023-factbook.pdf>). In contrast, at year-end 2019, 67% of hedge fund assets were held by institutional investors, according to the *Alternative Investment Management Association*, as cited in the Financial Times (2020), “Why Some Big Investors Have Had Enough of Hedge Funds” (<https://www.ft.com/content/71b5478c-3d40-11ea-b232-000f4477fbca>).

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our analysis to such dedicated marketers, the difference in annual flows increases to over 5%. Of the four potential causes tested for this bias, evidence supports two. The first is higher career mobility: women tend to align their career paths toward more promising funds. The second is emotional attraction: female CPs may have an advantage because hedge fund investors – predominantly men – may be drawn to them due to emotional appeal or direct attraction. As evidence of such preferences, we observe that the flows of hedge funds with female CPs are more strongly associated with the flows of funds of hedge funds managed by men than with those managed by women. Our findings highlight conflicts of interest in delegated investment management.

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# Chapter 1

## The Long and Short Leverage of Long/Short Equity Hedge Funds

### 1.1 Introduction

With USD 1.17 trillion of assets under management (“AUM”), long/short equity (“L/S equity”) hedge funds represent a quarter of the USD 4.51 trillion hedge fund industry.<sup>1</sup> L/S equity hedge funds attempt to take long positions in undervalued equity securities while selling short overvalued equity securities, exposing their portfolios to both equity-directional risk (“market risk”) and equity-spread risks (Fung & Hsieh, 2004a, 2004b, 2011). This chapter focuses on market-risk exposure (“market beta”), the dominant risk-factor exposure in these funds (e.g., Ardia et al., 2024, Table AVII). I find that approximately 35% of the variation in L/S equity returns can be explained by market beta.

It remains unclear how L/S equity hedge funds manage market beta in the short term. While hedge fund risk exposures are known to be dynamic (Bollen & Whaley, 2009; Patton & Ramadorai, 2013), empirical analyses on exposure changes are constrained by the infrequent reporting of hedge fund returns. Specifically, researchers estimate a fund’s market-risk exposure typically as the beta in a regression of fund returns on market-factor returns. Yet, since hedge fund net asset values (NAVs), from which returns are calculated, are generally determined by the fund administrator at only monthly frequency, beta-estimation windows usually need to span at least a year. The challenge lies in assessing market-risk exposure in real time. I measure market-risk exposure by net leverage, which, as I demonstrate, is a more accurate measure of current market-risk exposure than estimated betas. Because estimated betas are necessarily slow to adjust and contain stale information, net leverage is superior especially when market-risk exposure is volatile. The chapter documents four main findings.

First, monthly changes in market beta – as measured by net leverage – are economically relevant. A positive one-standard-deviation move in both market beta (15.56% per month) and excess market return (4.56% per month) implies an increase in monthly fund return by 0.71%, which is economically significant given an average monthly fund return of 0.81%. Funds that successfully manage market beta achieve

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<sup>1</sup>According to data vendor HFR, as of the end of Q4 2024. These numbers differ by vendor. Incorporating regulatory filings, Barth et al. (2023, Table 3) estimate that industry assets had reached USD 6 trillion already in 2019, with hedge funds of “Equity” strategy representing over a quarter of the industry.

significantly better performance than those that do not. However, I find no evidence of market-timing ability: Net-leverage changes are not informative about future market conditions, and the percentage of funds with significant market-timing skill is insignificant. This lack of evidence is unsurprising, given that L/S equity hedge funds are known to generate alpha from security selection rather than market timing (Fung & Hsieh, 2011). The economic relevance of market-beta dynamics, coupled with the apparent absence of market-timing ability, reinforces the question of how L/S equity hedge funds manage market beta.

Second, controlling for various fund-specific and economy-wide leverage and risk determinants, I demonstrate that fund managers allow net leverage to “drift” in response to (1) changes in the mark-to-market values of portfolio securities and (2) investor flows. In other words, changes in market prices, as well as inflows and outflows of investor capital determine the level of market beta.

Third, these passive leverage “drifts” provide an explanation for the procyclicality of market-risk exposures in L/S equity hedge funds observed in prior studies (Fung & Hsieh, 2004a, 2011). Similarly, net-leverage drifts cause exposure to the time-series momentum of equity indices, as captured by the *TSMOM\_EQ* factor of Moskowitz et al. (2012). This chapter thus offers an explanation for the *TSMOM\_EQ* exposure of L/S equity hedge funds observed most recently by Ardia et al. (2024).

Finally, while net leverage is allowed to fluctuate to an economically meaningful extent, it is also found to be autocorrelated and subject to mean reversion. The persistence of net leverage supports the notion that it is managed toward a target. Such targets are communicated to investors in the form of explicit ranges (such as “+/- 10% net leverage”) or labels (such as “long bias” or “market neutral”). I find that past market performance predicts fund managers’ *ex ante* choice of net leverage, with managers opting to launch funds with more aggressive net-leverage mandates when recent market performance has been strong. In line with the hypothesis that this behavior is motivated by investor demand, I find that it enables managers to raise more capital at fund inception. Strategically launching funds in this manner further contributes to the procyclicality of net leverage.

The remainder of this chapter is structured as follows. Section 1.2 describes the data. Section 1.3 argues that net leverage is a useful measure of market-risk exposure. Section 1.4 documents the economic relevance of monthly changes in net leverage. Section 1.5 demonstrates that net leverage is subject to drifts, while Section 1.6 discusses consequences of these drifts. Section 1.7 investigates the determinants of net-leverage targets. Finally, Section 1.8 concludes.

## 1.2 Data

This chapter analyzes a novel, hand-collected leverage dataset, which comprises 25,119 observations for the month-end long and short leverage levels of 432 L/S equity hedge funds between January 2000 and December 2022. Such time-series leverage data is rarely used in previous studies, because commercial hedge fund databases provide only static leverage information. To overcome this limitation, Liang and Qiu (2019) identify changes in reported leverage across historical database versions. However, such changes occur infrequently.<sup>2</sup> Other researchers study leverage dynamics at a lower frequency (Barth et al., 2020) or independent of fund risk (Ang et al., 2011; Avalos et al., 2015).

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<sup>2</sup>Liang and Qiu (2019) identify 421 changes in the reported average leverage of 10,448 funds between January 2002 and December 2017.

### 1.2.1 Data sources

**Hedge fund leverage** The leverage dataset was obtained through meticulous manual searches within fund documents provided by hedge fund firms over the period from 2000 to 2023. The documents have been provided voluntarily by the hedge fund firms, which could introduce a selection bias that inflates performance estimates. However, I document evidence for the absence of managerial activity. A positive selection bias should make it more difficult to find such evidence.

**Hedge fund returns and assets under management (AUM)** The base currencies of the 432 hedge funds in the sample are USD (334 funds), EUR (59), JPY (27), and GBP (12). Commercial monthly data on fund returns and AUM are retrieved in each fund’s respective currency from individual commercial databases (EurekaHedge, HedgeFund.net, and TASS) and the UNION dataset. The UNION dataset merges five commercial hedge fund databases: BarclayHedge, EurekaHedge, HFR, Morningstar, and TASS.<sup>3</sup> I manually search the UNION dataset and the individual databases for the name of each fund in the leverage dataset. I then compare the return data from these databases with the returns provided in the fund documents to verify consistency. If a fund has multiple share classes, I use the returns of the base-currency share class with the longest track record. I exclude data points pertaining to periods before the fund’s official launch, such as returns generated in a separate managed account that is later converted into a commingled fund.

The databases occasionally differ in the AUM values they report for a particular fund. To identify the correct AUM values of each fund, I manually compare and reconcile the AUM data from the databases with the figures provided in the fund documents. When applicable, I aggregate the AUM values from feeder funds to arrive at the master-fund AUM, which is the amount the hedge fund manager invests and is compensated on. If AUM and returns of a fund are in different currencies, I use end-of-month spot exchange rates to convert the AUM data to the particular base currency (as done in Joenväärä et al., 2022).

AUM series often remain stagnant over time. To address this problem, I first remove data points after a series has been unchanged for three consecutive months despite positive or negative fund performance. After this removal, which affects approximately 5% of AUM observations, I extrapolate AUM data for up to 11 months using fund returns. When calculating flows, I exclude extrapolated data and require a minimum of USD 5 million in AUM. To mitigate the effects of outliers, I winsorize the flows at the 0.5% and 99.5% levels. When logarithmizing AUM, I add USD 1 million to avoid extremely negative or undefined values.

**Hedge fund risk factors** I model L/S equity hedge fund returns using the five factors of Fama and French (2015) and the momentum factor (UMD) of Carhart (1997). The five factors are the excess market return (RMRF), which is the stock-market return minus the risk-free rate (RF); the “small-minus-big” (SMB) spread between stocks of small and large market capitalization; the “high-minus-low” (HML) spread between stocks of high and low valuation; the “robust-minus-weak” (RMW) spread between stocks of firms with strong and weak operating profitability; and the “conservative-minus-aggressive” (CMA) spread between stocks of conservatively and aggressively investing firms.

Since the hedge funds in the sample differ in their base currencies, I choose different versions of these factors depending on the fund’s currency. For USD-denominated funds, I follow Barth et al. (2020) and

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<sup>3</sup>See Agarwal et al. (2017) for details on the UNION dataset. The dataset has since been updated to include data through December 2022, and the BarclayHedge database has been added.

use the developed-market factors from Fama and French (2012), rather than those based solely on US equities, because the USD-denominated funds tend to manage portfolios of global securities. For funds with EUR, GBP, or JPY base currencies, which typically overweight investments in Europe or Japan, I replace the equity risk factors with local proxies for the European and Japanese markets. Specifically, I use the Japanese-market factors for JPY-denominated hedge funds and the European-market factors for EUR- and GBP-denominated hedge funds, as provided in Kenneth French’s data library.<sup>4</sup> The factors in the library are given in USD, and I convert them to EUR, GBP, or JPY to match the currency of the particular fund. Restricting the sample to USD-denominated hedge funds does not alter the chapter’s results.

### 1.2.2 Summary statistics

Table 1.1 summarizes the sample. Panel A describes the distribution of the main variables. Net leverage averages 39.4% across funds, which is similar to the 0.5 market beta observed by Fung and Hsieh (2011) for the average L/S equity hedge fund in the TASS database. Gross leverage ranges from 0% to 710.1%, with 0% gross leverage (i.e., 100% cash) being rare, observed almost exclusively immediately after fund launch and at the heights of the 2007–2009 subprime crisis. Median and mean gross leverage are moderate, at 129.1% and 138.2%, respectively, which is consistent with the limited use of leverage observed in L/S equity hedge funds by Barbarino (2009). Leverage is found to be highly autocorrelated, with average autocorrelations at the fund level ranging from 0.57 for net leverage to 0.65 for long leverage. The average fund achieves an after-fee (“net”) return of 0.81% and a CAPM alpha of 0.42% per month, manages USD 347.8 million of capital, and is 5.40 years old.

Panel B reports the number of funds and leverage observations by calendar year, fund currency, and fund launch year. The number of leverage observations per fund ranges from 10 to 256. Panel C presents correlation coefficients among the different measures of leverage. The positive correlation (0.435) between changes in long and short leverage supports the assumptions of Jiao et al. (2016), who expect managers to engage in hedging (unwinding) trades. These trades are characterized by simultaneous increases (decreases) in long and short leverage. Fund managers may make active management decisions to maintain desired net-leverage levels and to preserve hedging ratios among individual portfolio positions. In this context, Panel D shows transition matrices based on a fund’s net leverage, similar to those used by Bali et al. (2011). It reports the relative frequency with which funds transition from one net-leverage range to another between years  $y$  and  $y + 1$  (upper table) or between  $y$  and  $y + 2$  (bottom table). The tables suggest that net leverage is indeed persistent at the fund level.

### 1.2.3 Leverage levels over time

Figure 1.1 plots the average long, short, gross, and net leverage levels throughout the sample period. The salient feature of all time series is the positive correlation between leverage levels and the equity market. The grey areas mark peak-to-trough periods in the S&P 500 index of at least 10%. Equity-market drawdowns – such as those during the dot-com collapse and the subsequent events of September 11, 2001 (March 2000 to October 2002), the subprime crisis (October 2007 to March 2009), the COVID-19 epidemic (February and March 2020), or the 2022 monetary tightening – are associated with leverage reductions.

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<sup>4</sup>Kenneth French’s data library is available at <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>.

This positive association between hedge fund leverage and aggregate market returns has been documented in previous studies. Eichengreen and Park (2002) observe a decline in hedge fund gross leverage following the 1998 Russia/LTCM crisis. Leverage then rose to a local high in 2000, coinciding with the peak in equity prices, before decreasing during the 2000 NASDAQ crash (McGuire et al., 2005). After reaching a peak in mid-2007, leverage gradually declined throughout the subsequent subprime crisis of 2007-2009 (Ang et al., 2011; Liang & Qiu, 2019).

Section 1.3 demonstrates the close relationship between net leverage and market beta in L/S equity hedge funds. In line with this relationship and the evolution of net leverage observed in Figure 1.1, Fung and Hsieh (2011, p. 556) show that, after the internet bubble burst in March 2000, median L/S equity market betas fell “to a low of 0.30 in 2002–3, and then rising back to 0.43 in 2006–7” (see also Fung and Hsieh, 2004a, Figure 18). Sections 1.5, 1.6, and 1.7 offer two explanations for the observed procyclicality of net leverage (and consequently market beta): First, net leverage is subject to “drifts” (Section 1.5), which promote a positive correlation between market returns and net leverage (Section 1.6). Second, net-leverage targets are chosen based on recent market performance (Section 1.7).

### 1.3 Net leverage as a measure of market beta

Net leverage and market beta are closely related, but not identical. Any portfolio’s beta is the weighted sum of its individual asset betas. In the case of a L/S equity hedge fund, the portfolio consists of equity securities held long (the “long book”) and equity securities sold short (the “short book”). Since long and short leverage are the cumulative weights of those long and short securities, respectively, the portfolio beta of a L/S equity hedge fund can be calculated as the difference between the leverage-weighted long- and short-book betas:

$$\beta_P = LONG \times \beta_L - SHORT \times \beta_S = NET \times \beta_L - SHORT \times (\beta_L - \beta_S), \quad (1.1)$$

where  $\beta_P$ ,  $\beta_L$ , and  $\beta_S$  are the betas of the entire fund portfolio, its long book, and its short book, respectively.  $LONG$  ( $SHORT$ ) represents long (short) leverage, which is the market value of securities held long (sold short) divided by the fund’s AUM.  $NET$  (net leverage) is long minus short leverage. Thus, net leverage deviates from the true market beta whenever the long or short book has a market beta different from 1.

While these long- and short-book betas are not directly observable, Joenväärä et al. (2022) and Malakhov et al. (2024) find that hedge funds are exposed to the “betting-against-beta” (BAB) factor of Frazzini and Pedersen (2014). To exploit the leverage constraints of other market participants, L/S equity hedge funds may go long the BAB factor by taking long positions in low-beta securities while selling short high-beta securities (Pedersen, 2015, p. 141). When this is the case, long-book beta is lower than short-book beta and net leverage underestimates the true beta. Nonetheless, I argue that measuring market beta using net leverage has merit. I discuss two empirical arguments in the following two sections:

1. Across funds and over time, no evidence is found that long- or short-book betas differ from 1 (Section 1.3.1).
2. Measuring market beta with net leverage rather than with OLS-estimated betas produces lower estimation errors (Section 1.3.2).

### 1.3.1 Long- and short-book betas

**Fund-return model** The leverage data allows to estimate long- and short-book betas directly. To do so, I follow Fung and Hsieh (2011) in modeling the return of a L/S equity hedge fund as follows:

$$RET = (1 - LONG + SHORT) \times r_f + LONG \times r_L - SHORT \times r_S, \quad (1.2)$$

where  $RET$  is the net (after-fee) return of a L/S equity hedge fund,  $r_f$  is the return on the risk-free asset,  $r_L$  is the (unlevered) return on securities held long, and  $r_S$  is the (unlevered) return on securities sold short. The first term represents the payment of the risk-free rate on the sum of any cash amounts not used for purchases of long securities ( $1 - LONG$ ) and short-sale proceeds ( $SHORT$ ). Here, I assume, for simplicity, that both short-sale proceeds and cash posted as margin earn the risk-free rate.<sup>5</sup> According to the second and third terms, the investor further earns the returns on the long and short books, weighted by long and short leverage, respectively. The fund manager's objective is to maximize the return on the long book and to minimize the return on the short book.

Further following Fung and Hsieh (2011), with  $NET \equiv LONG - SHORT$ , Equation 1.2 can be rearranged as follows:

$$RET - r_f = NET \times (r_L - r_f) + SHORT \times (r_L - r_S), \quad (1.3)$$

where  $r_L - r_f$  and  $r_L - r_S$  represent compensation for bearing long-side and spread risks, respectively (Fung & Hsieh, 2011). Long-side returns scale with net leverage, while spread returns scale with short leverage. Leverage levels thus allow long-side returns to be separated from spread returns, and both types of returns to be unlevered.

**Regression model** To estimate the market betas of the long and short books, I regress monthly fund excess returns on interaction terms between various risk factors (market, size, value, etc.) and each of net leverage and short leverage. The regression model is specified as follows:

$$\begin{aligned} RET_{i,t} - RF_t = & NET_{i,t-1} \left( \beta_1 RMRF_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} \right. \\ & \left. + \beta_4 RMW_{i,t} + \beta_5 CMA_{i,t} + \beta_6 UMD_{i,t} \right) \\ & + SHORT_{i,t-1} \left( \beta_7 RMRF_{i,t} + \beta_8 SMB_{i,t} + \beta_9 HML_{i,t} \right. \\ & \left. + \beta_{10} RMW_{i,t} + \beta_{11} CMA_{i,t} + \beta_{12} UMD_{i,t} \right) \\ & + \sum_k \beta_{13}^k FUND\_FE_i^k + \sum_l \beta_{14}^l YMTH\_FE_t^l + \varepsilon_{i,t}, \end{aligned} \quad (1.4)$$

where  $RET_{i,t}$  is the return of fund  $i$  in month  $t$ .  $RF_t$  is the return on the risk-free rate, proxied by the US 1-month T-bill, in month  $t$ .  $NET_{i,t-1}$  and  $SHORT_{i,t-1}$  are the fund's net and short leverage at the previous month-end, respectively.  $RMRF_{i,t}$ ,  $SMB_{i,t}$ ,  $HML_{i,t}$ ,  $RMW_{i,t}$ ,  $CMA_{i,t}$ , and  $UMD_{i,t}$  are the month- $t$  returns of the Fama and French (2015) and Carhart (1997) factors.<sup>6</sup> Thus,  $\beta_1$  to  $\beta_6$  capture the sensitivity of the fund's (unlevered) long-side returns to the Fama-French and Carhart factors, while  $\beta_7$  to  $\beta_{12}$  capture the sensitivity of the fund's (unlevered) spread returns to the same factors.  $FUND\_FE_i$  and  $YMTH\_FE_t$  represent fund and year-month fixed effects, respectively.  $\varepsilon_{i,t}$  is the error term.

<sup>5</sup>As Pontiff (1996, p. 1139) explains, interest rates may be paid on only a fraction of short-sale proceeds. This fraction is negotiated with the prime broker. In a typical margin agreement at the time, a trader was paid interest on 75% of the short-sale proceeds.

<sup>6</sup>The risk factors depend on  $i$  as they differ by fund currency (see Section 1.2.1).

**Regression results** Table 1.2 reports the regression results. I find that L/S equity hedge funds incur market risk through positive net leverage ( $\beta_1$ ). The insignificant coefficient estimate for  $\beta_7$  suggests that the market beta of the short book is not significantly different from that of the long book. In other words, there is no evidence of exposure to the betting-against-beta (BAB) factor at the pooled level.<sup>7</sup> Furthermore, in Columns (1) and (2), the estimate for  $\beta_1$  is not significantly different from 1 ( $\chi^2 = 0.36$ ).<sup>8</sup> This result aligns with Griffin and Xu (2009, Table 2), who find no significant difference in beta between the 13F-reported long holdings of hedge funds and mutual funds. To summarize, in a pooled regression across funds and over time, no evidence is found that net leverage is not a one-to-one measure of market beta.

**Non-linearity** While the regression assumes a linear relationship, it remains possible that the relationship between net leverage and market beta exhibits non-linear patterns. For example, the difference between long- and short-book betas might be larger for high and low net-leverage levels and smaller for central levels. If this is true, the accuracy of net leverage as a beta measure would vary with net leverage. To investigate such potential non-linearities, Figure 1.2 shows binned scatterplots comparing average net leverage levels with estimated market betas. For each fund currency, observations are pooled across funds and sorted into 50 equal-sized groups based on the magnitude of net leverage. A market beta is then estimated for each group using a CAPM model, and the estimated beta is plotted against the group’s average net leverage. For example, for the EUR-denominated funds, the first group contains net-leverage observations ranging from  $-81.4\%$  to  $-12.7\%$ . The group’s average net leverage and its estimated market beta are  $-27.2\%$  and  $-0.304$ , respectively, indicating slightly higher short-book betas than long-book betas for this group.

Overall, the charts suggest a linear relationship between net leverage and estimated betas. Across groups, average net leverage explains 99.3% of the variation in estimated betas. These findings align with the regression results. There is no evidence that differences in long- and short-book betas cause net leverage to be a biased measure of market beta.

### 1.3.2 Forecasting power of net leverage

My second argument is practical: measuring market beta with net leverage produces lower estimation errors than using OLS-estimated betas. While OLS estimates account for differences between long- and short-book betas, they adjust slowly to changes in beta. Consequently, monthly changes in market beta remain largely unexplained by OLS estimates. In contrast, measuring market beta with net leverage reveals that these changes account for over 8% of the variation in fund returns.

I arrive at these two findings by comparing the predictive power of (A) OLS-estimated betas, (B) net leverage, and (C) fund-average net leverage, as competing measures of market beta. For each fund, I estimate a market beta in a CAPM model with no other factors, using a rolling window of 12 or 24 months. Then, I predict the fund returns in  $t + 1$  using the CAPM beta estimated from periods  $t - 11$  through  $t$  (for 12-month windows) or  $t - 23$  to  $t$  (for 24-month windows). Next, I predict the  $t + 1$ -returns using net leverage at the end of period  $t$  as the measure of market exposure. Finally, I predict the returns

<sup>7</sup>Table AVII in Ardia et al. (2024) indicates that the positive exposure of hedge funds to the BAB factor is driven by “Relative Value” and “Event Driven” hedge funds. For the L/S equity strategy, the factor may be relevant for the minority of market-neutral funds, which could explain why the  $\beta_7$  coefficient (while insignificant) is positive.

<sup>8</sup>The estimate for  $\beta_1$  differs from 1 in Columns (3) and (4), likely due to the negative correlation between *CMA* and *RMRF* (see Fama & French, 2015, Table 4, Panel C).

in  $t + 1$  using the fund's average net leverage. Specifically, I compare the root-mean-square errors (RMSE) of the following three models:

$$(A) \quad RET_{i,t+1} - RF_{t+1} = \beta_{h,i,t} \times RMRF_{i,t+1} + \varepsilon_{i,t+1}, \quad (1.5)$$

$$(B) \quad RET_{i,t+1} - RF_{t+1} = NET_{i,t} \times RMRF_{i,t+1} + \varepsilon_{i,t+1}, \quad (1.6)$$

$$(C) \quad RET_{i,t+1} - RF_{t+1} = \overline{NET}_i \times RMRF_{i,t+1} + \varepsilon_{i,t+1}. \quad (1.7)$$

Here,  $\beta_{h,i,t}$  is the estimated market beta of fund  $i$  in month  $t$ , and  $h$  is the number of months used in the rolling estimation window for  $\beta_{h,i,t}$ . This variable  $h$  is set to either 12 or 24 months.  $RMRF_{i,t+1}$  is the excess return in  $t + 1$  of the market relevant to fund  $i$ .  $NET_{i,t}$  is the net leverage of fund  $i$  at the end of month  $t$ , and  $\overline{NET}_i$  is the fund's average net leverage. In each month, observations are separated into four groups based on the standard deviation of net leverage during the estimation window of  $\beta_{h,i,t}$ .

Table 1.3 reports the results. Comparing models (A) and (B), I find that net leverage significantly improves the model fit. Measuring market beta through net leverage rather than with OLS-estimated betas produces lower root-mean-square errors. As expected, the superiority of net leverage increases with the volatility of net leverage: the reduction in RMSE is at least eight times as large if net-leverage volatility is in the top quartile (Q4) compared to the lowest quartile (Q1). The differences are economically meaningful as, in the top quartile of net-leverage volatility, net leverage reduces the Mean Absolute Error by 0.25% (12-month windows) and 0.26% (24-month windows) (not reported). The explanatory power, measured as  $R^2$ , is 16.6 (12-month windows) or 15.9 (24-month windows) percentage points higher in Q4. The difference in  $R^2$  between (B) and (C) implies that 8.6 (12-month) or 8.5 (24-month) percentage points of variation in fund returns can be attributed to changes in market exposure. Failing to capture these monthly changes, estimated betas are comparable in terms of explanatory power to average net leverage. I conclude that net leverage is a viable alternative to study the short-term (month-to-month) dynamics of hedge fund market-risk exposure.

## 1.4 Net-leverage changes are relevant

The previous Section 1.3 found that over 8% of the variation in L/S equity hedge fund returns can be attributed to deviations from average market exposure. What is the economic impact of these deviations? To investigate, I follow Lo (2008) in decomposing the expected return of a fund's portfolio into attributions from "Security Selection", "Factor Timing", and "Risk Premia":

$$\begin{aligned} E[RET] &= \text{Security Selection} + \text{Factor Timing} + \text{Risk Premia} \\ &= \sum_{j=1}^n \alpha_j E[\omega_j] + \sum_{k=1}^K \text{Cov}(\beta_{Fk}, F_k) + \sum_{k=1}^K E[\beta_{Fk}] E[F_k]. \end{aligned} \quad (1.8)$$

Here, the fund is invested in  $n$  securities with weights  $\omega$  and exposed to  $K$  risk factors with betas  $\beta_F$ . Fund returns are generated by the securities' deviations from the linear factor model ("Security Selection"), by positive covariance between portfolio betas and factor realizations ("Factor Timing"), and static factor exposures ("Risk Premia") (Lo, 2008). Using this framework, I focus on the market factor and measure the market-timing ability of a fund as the covariance of its market-risk exposure, proxied by its net leverage at prior month-end, with the current-month market excess return:

$$\begin{aligned} \text{Market Timing Ability}_i &= \text{Cov}(NET_{i,t-1}, RMRF_{i,t}) \\ &= E[(NET_{i,t-1} - \overline{NET}_i)(RMRF_{i,t} - \overline{RMRF}_i)]. \end{aligned} \quad (1.9)$$

$\overline{NET}_i$  and  $\overline{RMRF}_i$  denote the mean net leverage and mean market excess return of fund  $i$ , respectively. The net leverage of a successful market timer deviates positively (negatively) from its mean whenever the market subsequently outperforms (underperforms) (e.g., Busse, 1999; Cao et al., 2013).

Table 1.4 shows that the funds in the top quintile of market-timing ability exhibit an average covariance between net leverage and market returns of 0.28%, which means that these managers generate an additional 0.28% of return per month through net-leverage adjustments (an economically significant 3.38% per annum). As expected, funds with better market-timing ability outperform: the difference in returns between top- and bottom-quintile “market timers” is 0.46% per month, which is statistically significant at the 1% level with a  $t$ -statistic of 3.10. This return difference translates into higher CAPM, Fama-French, and Fung-Hsieh alphas for the top-quintile “market timers”.<sup>9</sup>

What proportion of funds demonstrate timing ability? For each fund, I analyze the statistical significance of its market-timing ability divided by the variance of its net leverage. This quotient is equal to the beta of a univariate regression of the market risk premium on net leverage. Market-risk exposure is thus a linear function of future market conditions, which is in line with the timing literature (e.g., Admati et al., 1986; Ferson and Schadt, 1996). I find that only 6.0% (9.6%) of the funds exhibit significant skill, defined as the beta estimate being different from zero at the 5% (10%) significance level. These fractions are statistically insignificant with  $p$ -values of 19% and 60%, respectively, assuming an independent Bernoulli distribution as in Chen and Liang (2007).<sup>10</sup>

## 1.5 Net leverage is subject to “drifts”

Section 1.3 found that monthly changes in net leverage are economically relevant for fund returns, yet Section 1.4 found no evidence of market-timing skill. In this section, I explore alternative determinants of monthly net-leverage changes. I show that net leverage is subject to “drifts”: managers allow net leverage to fluctuate naturally with mark-to-market effects and investor flows.

### 1.5.1 Intuition

Net leverage is equal to long leverage minus short leverage. Long and short leverage are increased (+) and decreased (−) by three factors:

1. *Trading*: long buying (+) and long selling (−) in case of long leverage; short selling (+) and short covering (−) in case of short leverage.
2. *Mark-to-market effects*: movements in the prices of portfolio securities (+ or −).
3. *AUM flows*: inflows (−) and outflows (+) of investor capital.

I argue that the latter two factors – mark-to-market effects and AUM flows – are important. To illustrate, consider the very first L/S equity hedge fund, established by Alfred Jones in 1949. With USD 100,000 of client capital (AUM), Jones would “borrow perhaps another USD 50,000. [...] Of the USD

<sup>9</sup>For the Fung-Hsieh alphas, the returns on the model’s trend-following factors and the Datastream codes for the remaining factors are taken from David A. Hsieh’s data library: <https://people.duke.edu/~dah7/HFRFData.htm>.

<sup>10</sup>For example, for the 5% level,  $t = (0.06 - 0.05) / \sqrt{0.05 \times (1 - 0.05) / 365} = 0.88$ , which is insufficient to reject the null hypothesis that all timing-ability coefficients are zero.

150,000 total, he might put USD 110,000 into stocks he likes and sell short USD 40,000 of stocks he thinks are overvalued” (Loomis, 1966, p. 240). Jones’ portfolio would exhibit the following leverage levels:

$$\begin{aligned} \text{Long leverage} &= \text{USD } 110,000 / 100,000 = 110\%, \\ \text{Short leverage} &= \text{USD } 40,000 / 100,000 = 40\%, \\ \text{Net leverage} &= \text{USD } 70,000 / 100,000 = 70\%, \\ \text{Gross leverage} &= \text{USD } 150,000 / 100,000 = 150\%. \end{aligned}$$

*Mark-to-market effects:* First, if the stock market depreciates by 10% and all stocks in Jones’ portfolio fall by 10% as well, then the long portfolio will depreciate in value to USD 99,000, and the short portfolio will shrink to USD 36,000. As a result, AUM decline from USD 100,000 to USD 93,000.<sup>11</sup> Long leverage decreases from 110% to 106.5%, while short and net leverage decline to 38.7% and 67.7%, respectively. Thus, judging by net leverage, Jones’ market-risk exposure would decrease due to negative performance, assuming no intervention.

*AUM flows:* Second, if Jones instead receives an inflow of another USD 20,000 of client capital, AUM would increase from USD 100,000 to USD 120,000. If Jones does not react, then long leverage decreases from 110% to 91.7%, while short and net leverage decrease to 33.3% and 58.3%, respectively.

Why might fund managers not intervene against such leverage “drifts”? L/S equity hedge fund managers typically base their investment decisions on a fundamental analysis of a firm’s longer-term prospects, considering such factors as its indebtedness, competitive position, or quality of management. In the absence of (illegal) exploitation of material private information, this approach suggests longer holding periods of individual securities. Indeed, studies analyzing quarterly information from 13F filings observe a median annual trading turnover for hedge fund long stock positions of approximately 100% (Brunnermeier & Nagel, 2004; Griffin & Xu, 2009). Long investment horizons and low trading frequency may lead to a more cavalier treatment of leverage drifts.

## 1.5.2 Calculation of leverage drifts

I introduce a variable “*DRIFT*” that captures net-leverage changes due to flows and mark-to-market effects:

$$DRIFT_{i,t} \equiv \frac{AUM_{i,t-1}}{AUM_{i,t}} (NET_{i,t-1} + RET_{i,t} - RF_t + NET_{i,t-1} \times RF_t) - NET_{i,t-1}. \quad (1.10)$$

I derive *DRIFT* as follows. First, the net leverage of a fund  $i$  at month  $t$  is the difference between its long and short leverage. Long leverage (short leverage) is given by the dollar value of the long portfolio (short portfolio) divided by the AUM:

$$NET_{i,t} = LONG_{i,t} - SHORT_{i,t} = \frac{\$LONG_{i,t} - \$SHORT_{i,t}}{AUM_{i,t}}. \quad (1.11)$$

Second, from the end of month  $t - 1$  to the end of month  $t$ , the dollar values of the long and short books increase by the respective returns on the long and short books,  $r_L$  and  $r_S$ . The long and short books also change due to the manager’s intra-month trading (long buying, long selling, short selling, and

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<sup>11</sup>AUM is calculated as (in thousands of US dollars): 99 (long portfolio) – 36 (short portfolio) – 50 (debt owed) + 40 (remaining borrowed cash) + 40 (short-sale proceeds). Stock-loan fees, dividends, interest, fund fees and expenses, and other noise are ignored in this illustration.

short covering), as well as the returns generated on securities bought and sold during the month. I collect these intra-month effects in a variable *Trading*:

$$NET_{i,t} = \frac{\$LONG_{i,t-1}(1 + r_{L,i,t}) - \$SHORT_{i,t-1}(1 + r_{S,i,t})}{AUM_{i,t}} + Trading_{i,t}. \quad (1.12)$$

Using Equation 1.2 and simplifying,

$$NET_{i,t} = \frac{AUM_{i,t-1}}{AUM_{i,t}} (NET_{i,t-1} + RET_{i,t} - RF_t + NET_{i,t-1} \times RF_t) + Trading_{i,t}. \quad (1.13)$$

I define the *DRIFT* in net leverage as the change in net leverage that is not due to trading:

$$\Delta NET_{i,t} = NET_{i,t} - NET_{i,t-1} = DRIFT_{i,t} + Trading_{i,t}. \quad (1.14)$$

Note that *DRIFT* does include the effect of fund flows. Specifically, during the month, fund AUM increase by the fund's net return (*RET*) and by the difference between inflows and outflows:  $AUM_{i,t} = AUM_{i,t-1}(1 + RET_{i,t}) + Inflows - Outflows$  (Sirri & Tufano, 1998). Inflows (investor subscriptions) and outflows (redemptions) change the cash position of the fund. As illustrated: if the manager does not react (by investing inflows or, in case of redemptions, by liquidating positions), then inflows reduce long and short leverage, and outflows increase it.<sup>12</sup> I winsorize *DRIFT* at the 0.5% and 99.5% levels to mitigate the influence of AUM reporting errors and outliers.

### 1.5.3 Regression model

I next explore the relevance of leverage drifts using a pooled OLS regression. Similar to Ang et al. (2011), I specify that monthly changes in net leverage are determined by both fund-specific and economy-wide factors:

$$\begin{aligned} \Delta NET_{i,t} = & \beta_1 DRIFT_{i,t} + \beta_2 NET_{i,t-1} + \beta_3 |RET_{i,t}| \\ & + \sum_k \beta_4^k FUND\_FE_i^k + \sum_l \beta_5^l FUND\_CTRLS_{i,t}^l + \sum_m \beta_6^m MACRO\_CTRLS_t^m + \varepsilon_{i,t}, \end{aligned} \quad (1.15)$$

where  $\Delta NET_{i,t}$  is the change in net leverage of fund  $i$  in month  $t$ . The explanatory variable of interest, *DRIFT*, captures net-leverage changes due to flows and due to marking the portfolio to market.  $NET_{i,t-1}$  is net leverage at the previous month-end, included to account for the mean-reversion attributes of leverage found by Ang et al. (2011). The absolute fund return,  $|RET|$ , is included to control for potential reverse causality (higher net leverage causing higher absolute fund returns). I further control for (1) time-invariant fund characteristics using fund fixed effects (*FUND\_FE*), (2) time-varying fund variables (*FUND\_CTRL*S), and (3) macro factors (*MACRO\_CTRL*S). Table 1.5 summarizes the leverage determinants considered. Standard errors are clustered by fund and year-month.

### 1.5.4 Regression results

Table 1.6 reports the regression results. *DRIFT* is an economically and statistically significant determinant of net-leverage changes. Across model specifications, the coefficient estimate for *DRIFT* ranges from

<sup>12</sup>In their offering documents, hedge funds usually reserve the right to satisfy redemptions "in kind". Redemption proceeds are then paid to the investor in portfolio securities or shares of a "special purpose vehicle", not in cash (Aiken et al., 2015). Absent extreme market environments and fund liquidations, this is not the norm in practice and is generally performed less frequently by L/S equity hedge funds than by hedge funds trading in less liquid securities than common stock.

0.15 to 0.30 and is statistically significant at the 1% level, with  $t$ -statistics of 3.18 or higher. In Panel A, Column (1) presents a model with only four explanatory variables: *DRIFT*, fund fixed effects, net leverage at prior month-end ( $NET(t-1)$ ), and absolute fund returns ( $|RET|$ ). *DRIFT* marginally improves the explanatory power: excluding *DRIFT* would result in a 0.46 percentage-point decrease in adjusted  $R^2$ . Next, I include additional control variables to verify the robustness of the regression results.

**Control factors for fund-specific leverage determinants** Previous studies found that hedge fund leverage and risk are influenced by fund-specific supply and demand dynamics. On the supply side, counterparties' willingness to provide leverage depends on fund characteristics such as the fund's operational risk, performance, portfolio and investor liquidity, investment style, and size (Barth et al., 2020; Brown et al., 2008, 2009, 2012; Brown et al., 2001; Eichengreen & Park, 2002; Liang & Qiu, 2019). Although these factors are more relevant for gross leverage than for net leverage, I control for them in Column (2). Specifically, in addition to fund fixed effects, I include as covariates: cumulative 12-month fund returns, including the current month (i.e., from  $t-11$  to  $t$ ) ( $RET12$ ), fund-return volatility over the same period ( $VOL12$ ), the logarithm of fund AUM at month-end  $t$  ( $\log(AUM)$ ), and fund flows during month  $t$  ( $FLOW1$ ) and over the period  $t-2$  to  $t$  ( $FLOW3$ ). The relevance of *DRIFT* is robust to the inclusion of these factors.

On the demand side, mainly two fund-specific traits influence hedge fund leverage and risk. First, fund managers might follow incentives to achieve a level of risk that maximizes their personal payoff in terms of management- and incentive-fee income. Here, the non-linearity of the compensation contract and "put options" in the hands of service providers and investors constrain the liberty of hedge fund managers to employ leverage and might lead the managers to engage in risk-shifting (Buraschi et al., 2014; Dai & Sundaresan, 2009; Kolokolova & Mattes, 2018; Liu & Mello, 2011; Xiao, 2018; Yin & Zhang, 2022).

To control for risk-shifting, I test whether fund risk – as measured by net leverage – is influenced by the distance to the high-water mark ( $DIST2HWM$ ).  $DIST2HWM$  is the AUM-weighted average distance from the Net Asset Value (NAV) to the high-water mark (HWM). It represents the moneyness of the compensation contract.<sup>13</sup> I follow Buraschi et al. (2014) in this analysis, with the key difference that I use net leverage to measure risk, rather than rolling betas or rolling volatilities. Net leverage arguably provides a more accurate representation of the risk currently desired by the manager. The model of Buraschi et al. (2014) predicts a bell-shaped relationship between risk and  $DIST2HWM$ , with the peak of the bell located between the HWM and the strike price of the short put options. This strike price is estimated at a  $-20\%$  drawdown from the HWM for most hedge fund strategies. The bell shape implies two slope-sign changes below and above the HWM. The empirical test is simpler: following Buraschi et al. (2014, Table XI), I employ a piecewise linear regression model that distinguishes between positive and negative values of  $DIST2HWM$ . Risk is expected to be reduced as the NAV moves away from the HWM in either direction. Maximum risk should thus be observed when  $DIST2HWM = 0$ . As in Buraschi et al. (2014), I include changes in the CBOE VIX ( $\Delta VIX$ ) level to control for the possibility that market-wide shocks influence risk-taking behavior. The results reported in Columns (3) and (4) provide mixed evidence of risk-shifting. In Column (3), as predicted by Buraschi et al. (2014), the manager decreases risk as the fund value rises above the HWM ( $DIST2HWM \geq 0$ ), presumably to lock in the performance fee. Conversely, if the fund value falls below the HWM ( $DIST2HWM < 0$ ), the manager reduces risk to ensure the fund's survival.

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<sup>13</sup>  $DIST2HWM$  is calculated under the assumptions that (1) when a fund receives inflows, a new share class is created with a HWM equal to the fund's current NAV, and (2) outflows are subject to the average HWM (Buraschi et al., 2014).  $DIST2HWM$  is necessarily imprecise because only net flows are observed.

However, Column (4) shows that these results are not robust to the inclusion of lagged risk-taking as an explanatory variable (e.g., as in Yin and Zhang, 2022), suggesting that the results in Column (4) could be due to mean reversion and reverse causality (i.e., more extreme *DIST2HWM* values are caused by higher risk, which in turn is more likely to be reduced). The relevance of *DRIFT* remains robust.

A second fund-specific determinant of leverage is that fund managers might try to “time the market”: they may discretionarily set their leverage and risk levels to exploit the future market environment, which they anticipate in terms of market or industry return, factor performance, cycle, volatility, liquidity, or sentiment (Bali et al., 2014; Bali et al., 2021; Cao et al., 2013; Chen & Liang, 2007; Crego & Gálvez, 2021; Li & Shawky, 2014; Osinga et al., 2021; Zheng et al., 2018). To test for various forms of market-timing skill, I include the current- and next-month market excess return (*RMRF*), the current- and next-month change in market-wide volatility as measured by the CBOE VIX ( $\Delta VIX$ ), and the current- and next-month change in market-wide liquidity as measured by the Pástor and Stambaugh (2003) liquidity measure ( $\Delta LIQ$ ) in Columns (5) and (6).<sup>14</sup> While the current-month factors exhibit the expected signs – net leverage rising with market return and liquidity, and falling with market volatility – I find no evidence of market-timing ability. *DRIFT* remains robust to the inclusion of these factors.

**Control factors for economy-wide leverage determinants** Macro determinants outside the portfolio manager’s control – such as macroeconomic uncertainty, the cost of leverage, the creditworthiness of prime brokers (i.e., investment banks) as leverage providers, and industry-wide redemptions – affect the manager’s ability and willingness to apply leverage and take risks (Ang et al., 2011; Lambert & Platania, 2020; Liang & Qiu, 2019; Racicot & Théoret, 2013, 2016, 2018; Savona, 2012).<sup>15</sup>

To control for macro determinants, I follow Ang et al. (2011) and iteratively include the following macro factors in Columns (1) to (5) of Panel B: investment-bank (“IB”) stock returns (*IB.RET*) and CDS spreads (*IB.CDS*), the S&P 500 return (*SPX*), the level of the CBOE VIX (*VIX*), the LIBOR rate (*LIBOR*), the TED spread (*TED*), the term spread between 10-year US T-notes and 3-month US T-bills (*TED*), and aggregate capital flows into the hedge fund industry over the prior three months (*AGGFLOW*).<sup>16</sup> In line with expectations, IB counterparty risk, proxied by IB stock returns and IB CDS spreads, is negatively associated with changes in net leverage (Column 1). Leverage is positively associated with the state of the equity market (Column 2), which aligns with Racicot and Théoret (2013, 2016, 2018), who demonstrate that hedge fund risk increases during economic expansions and decreases during economic contractions and periods of macroeconomic uncertainty (as measured by the VIX). LIBOR and TED spread have negative effects on net-leverage changes (Column 3). Beyond increasing the cost of leverage, a rise in interest rates (such as LIBOR) may also signal stock-market deterioration, prompting hedge funds to reduce risk (Racicot & Théoret, 2013). The TED spread can serve as a proxy for systemic risk (Bianchi et al., 2010).

The negative effects of VIX and the TED spread are consistent with the findings of Liang and Qiu (2019) on the leverage of newly established hedge funds. In unreported results, I find that the relevance of

<sup>14</sup>The liquidity-measure data is available on Robert Stambaugh’s website: <https://finance.wharton.upenn.edu/~stambaug/>.

<sup>15</sup>I include these macro factors for completeness, noting that they are more likely to affect gross rather than net leverage. Moreover, L/S equity hedge funds rarely rely on the provision of “funding leverage” (McGuire & Tsatsaronis, 2008) by their prime brokers: 67% of long-leverage observations in my sample are below 100%. Since leverage can also be obtained through implicitly levered derivatives, such as options or CFDs (“instrument leverage”), funding leverage is required in even fewer than 33% of observations.

<sup>16</sup>Following Ang et al. (2011), *AGGFLOW* is calculated using industry-wide AUM data and hedge fund index returns from BarclayHedge: <https://www.barclayhedge.com/databases/global-database>.

aggregate hedge fund flows (*AGGFLOW* in Column 4) is limited to the subprime market crisis (October 2007 to March 2009). The decrease in hedge fund leverage during this crisis was accompanied by significant outflows from the industry: BarclayHedge reports that between June 2008 and March 2009, hedge fund industry assets almost halved, from USD 2,349 billion to USD 1,164 billion. During the crisis, a 1% industry outflow is associated with a 0.16% decrease in net leverage. This relationship supports theories suggesting that coordinated redemptions can force hedge funds into involuntary deleveraging (Liu & Mello, 2011). Despite the high correlation among some of the macro factors (see Panel C of Table 1.2), the results generally persist when I include all macro variables in a single regression (Column 5). Overall, these macro-factor results lend support to the main finding of Ang et al. (2011), namely that hedge fund leverage is driven by macro determinants. The results also support Avalos et al. (2015), who find that leverage decreases with perceived market risk and borrowing costs. Finally, *DRIFT* remains robust to controlling for macro factors via time fixed effects (Column 6).

In summary, I find that *DRIFT* is both economically and statistically significant in explaining changes in net leverage. These results remain robust after accounting for various fund-specific and macroeconomic factors.

### 1.5.5 Further robustness tests

Table 1.7 reports the results of robustness tests addressing three concerns about correlated predictors, omitted variables, and reverse causality. The first concern is that *DRIFT* could influence net-leverage changes solely through its correlation with lagged net leverage. To address this concern, Column (1) separates observations based on whether *DRIFT* and lagged net leverage have identical or opposing signs. (Since leverage is positive by definition, *DRIFT* differs in sign from lagged net leverage whenever it is negative.) The results show that *DRIFT* is significantly positively associated with leverage changes, even when the direction of this association contradicts mean reversion. This suggests that the relevance of *DRIFT* is not merely an artifact of its correlation with lagged leverage.

Second, the effect of *DRIFT* could stem from its positive correlation with fund returns. For instance, fund returns might influence a manager's risk aversion in such a way that the manager discretionarily adjusts net leverage in the same direction as dictated by *DRIFT*. However, Column (2) shows that *DRIFT* determines net-leverage changes in the predicted direction, even when this direction is contrary to such discretionary procyclical risk management (proxied by fund returns). Furthermore, Column (3) demonstrates that *DRIFT* is robust to the inclusion of fund return as an additional explanatory variable.

Third, *DRIFT* in most cases depends positively on the market return, allowing for two alternative explanations. First, managers may set leverage levels discretionarily in response to market returns. Second, the unclear timing of variables in month  $t$  allows for a reverse-causality story in which managers skillfully adjust long and short leverage in anticipation of future market environments ("market timing"). For example, a manager might increase long and decrease short leverage at the start of month  $t$  in anticipation of higher equity-market returns later in the same month. In this scenario, leverage changes would precede market returns, rather than be caused by them. Addressing both of these alternative stories, Column (4) suggests that the findings are robust: *DRIFT* has the expected effects, regardless of whether its direction aligns with that of the market.

**Long- and short leverage drifts** To gain a deeper understanding of how *DRIFT* influences net leverage, I decompose it into its long- and short-leverage components, denoted by *DRIFT<sub>L</sub>* and

$DRIFT\_S$ , respectively, and repeat the robustness tests for each component separately. The remaining Columns (5) to (12) in Table 1.7 report the results.  $DRIFT\_L$  and  $DRIFT\_S$  are estimated analogously to Section 1.5.2 as follows:

$$DRIFT\_L \equiv \frac{AUM_{i,t-1}}{AUM_{i,t}} \times LONG_{i,t-1}(1 + r_{L,i,t}) - LONG_{i,t-1}, \quad (1.16)$$

$$DRIFT\_S \equiv \frac{AUM_{i,t-1}}{AUM_{i,t}} \times SHORT_{i,t-1}(1 + r_{S,i,t}) - SHORT_{i,t-1}. \quad (1.17)$$

Calculating  $DRIFT\_L$  and  $DRIFT\_S$  requires estimates of the long- and short-book returns ( $r_L$  and  $r_S$ ). To arrive at these estimates, I first express each of  $r_L$  and  $r_S$  as a combination of the market excess return and an unknown alpha:  $r_{L,i,t} - RF_t = RMRF_{i,t} + \alpha_{L,i,t}$  and  $r_{S,i,t} - RF_t = RMRF_{i,t} - \alpha_{S,i,t}$ . Under the simplifying assumption that, while portfolio managers may differ in skill, each portfolio manager consistently generates the same amount of alpha on the long side as on the short side ( $\alpha_{L,i,t} = \alpha_{S,i,t}$ ), the average of the long- and short-book returns equals the market return:  $RMRF_{i,t} = (\hat{r}_{L,i,t} + \hat{r}_{S,i,t})/2 - RF_t$ . The long- and short-book returns for each fund  $i$  and month  $t$  can then be calculated using Equation 1.2.

Columns (5) to (8) refer to  $DRIFT\_L$ , and Columns (9) to (12) refer to  $DRIFT\_S$ . Both  $DRIFT\_L$  and  $DRIFT\_S$  have the expected positive effects on changes in long and short leverage, respectively. Notably,  $DRIFT\_S$  is positive but statistically insignificant when it depends positively on short leverage (Column 9). Because leverage is positive by definition,  $DRIFT\_S$  takes on the opposite sign from lagged short leverage when it is negative, as mentioned. That is, I find no statistically significant evidence that leverage drifts can increase short leverage. *Ad hoc* explanations point to risk-management considerations: as Ineichen (2001) clarifies, selling short is not the opposite of buying long. An adverse price movement in a long position leads to a more defensive positioning: the maximum (additional) potential loss on the position, as well as the position itself, become smaller. Adverse price changes in short positions, on the other hand, lead to more aggressive positioning: the position becomes larger, and losses remain potentially unlimited. From a risk-management perspective, the hedge fund manager might therefore be more inclined to intervene after losses on the short side than after gains on the short side, or either gains or losses on the long side. Stock-loan fees, the risk of a short squeeze or recall event, and the potential need to post additional margin further increase this incentive to manage short positions more actively than long positions.<sup>17</sup> To summarize, I find that  $DRIFT$  drives net leverage through both long and short leverage. In line with risk-management considerations, the effect of  $DRIFT\_S$  is limited to decreases in short leverage.

## 1.6 Drifts cause exposure to time-series momentum

Managers who allow net leverage to drift tend to passively engage in a trend-following strategy. In the absence of flows, Equation 1.10 simplifies to:

$$DRIFT_{i,t} = (RET_{i,t} - RF_t)(1 - NET_{i,t-1})/(1 + RET_{i,t}). \quad (1.18)$$

This equation shows that net-leverage drifts ( $DRIFT$ ) increase with fund returns, except in the uncommon case of a fund being levered long ( $NET_{i,t-1} > 1$ ). Since net leverage is positive in 93% of

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<sup>17</sup>Another potential venue is the positive gamma of put options used for hedging purposes: the delta-adjusted short leverage of long put positions decreases (in absolute terms) if the underlying appreciates.

observations, fund returns – and thus *DRIFT* – typically increase with market returns. As a result, *DRIFT* promotes a positive relationship between market returns and net leverage: net leverage rises and falls with the market.<sup>18</sup>

Consequently, allowing net leverage to drift should expose a fund to the time-series momentum (*TSMOM*) of the equity market (*TSMOM\_EQ*), as defined by Moskowitz et al. (2012). The *TSMOM* factors are based on a 12-month time-series momentum strategy with a 1-month holding period. Unlike cross-sectional momentum measures, such as *UMD* (Carhart, 1997), *TSMOM* is not a relative measure; it focuses solely on a security’s own past returns.

To test whether *DRIFT* leads to *TSMOM* exposure, I first separate all observations with sufficient prior data into five groups based on the beta of net leverage to *DRIFT*. Specifically, for each fund, I regress its changes in net leverage on *DRIFT* over 12-, 18-, or 24-month rolling horizons and record the estimated *DRIFT* betas. Next, I regress all fund returns on the interaction terms between *TSMOM\_EQ* and a dummy variable for the *DRIFT*-beta group (*Low*, *MediumLow*, *Medium*, *MediumHigh*, or *High*). Here, *TSMOM\_EQ* represents the monthly excess return of the *TSMOM* factor for global equity indices.<sup>19</sup> I include fund fixed effects and equity risk factors (*RMRF*, *SMB*, *HML*, *RMW*, *CMA*, and *UMD*) as control variables and cluster standard errors by fund and date. The regression is specified as follows:

$$\begin{aligned}
 RET_{i,t} - RF_t = & \beta_1 RMRF_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} \\
 & + \beta_4 RMW_{i,t} + \beta_5 CMA_{i,t} + \beta_6 UMD_{i,t} \\
 & + \beta_7 TSMOM\_EQ_t \times Low_{i,t} \\
 & + \beta_8 TSMOM\_EQ_t \times MediumLow_{i,t} \\
 & + \beta_9 TSMOM\_EQ_t \times Medium_{i,t} \\
 & + \beta_{10} TSMOM\_EQ_t \times MediumHigh_{i,t} \\
 & + \beta_{11} TSMOM\_EQ_t \times High_{i,t} \\
 & + \sum_k \beta_{12}^k FUND\_FE_i^k + \varepsilon_{i,t}.
 \end{aligned} \tag{1.19}$$

The results reported in Table 1.8 suggest that fund returns depend more strongly on *TSMOM\_EQ* as the *DRIFT* beta increases. The coefficient estimates (for  $\beta_7$  to  $\beta_{11}$ ) rise with the *DRIFT* group. The difference in coefficients ( $\beta_{11} - \beta_7$ ) is positive and statistically significant across all horizons, with  $\chi^2$  statistics of 6.7 and above. Allowing net leverage to drift exposes fund returns to time-series momentum. Thus, *DRIFT* provides an explanation for L/S equity hedge funds’ exposures to time-series momentum, which were observed by Chevalier and Darolles (2019, Table 11) and Ardia et al. (2024, Tables IX and AVII).

## 1.7 Net-leverage targets are chosen strategically

Section 1.3 showed that at least 26% of the variation in a L/S equity hedge fund’s returns is explained by the fund’s average, or “passive,” market exposure. This passive exposure is unlikely to be determined

<sup>18</sup> Assuming that the market return (*RM*) affects the fund return (*RET*) only through net leverage (*NET*), then, for positive values of *NET*, the relationship between *DRIFT* and *RM* is strongest when *NET* is around 0.5, which aligns with the typical level for long/short equity hedge funds (see Section 1.2.2).

<sup>19</sup> Data on the *TSMOM\_EQ* factor are obtained from AQR: <https://aqr.com/Insights/Datasets>.

randomly. Instead, the mean reversion, persistence, and autocorrelation of net leverage, along with the high correlation between changes in long and short leverage, suggest that net leverage is managed toward a target. Indeed, L/S equity hedge funds usually commit themselves to containing net leverage within certain ranges. They do so by specifying an explicit net-leverage range or by assigning labels to the fund, such as “short biased,” “market neutral,” “low net,” or “long bias.” How do fund managers decide which net-leverage range to commit to?

Deducing these ranges from observed net-leverage levels can be problematic because net leverage is determined endogenously. Therefore, I rely on a separate sample drawn from a 2024 version of the EurekaHedge database. The sample includes all USD-denominated hedge funds in the database that follow a “Long Short Equities” strategy. Duplicate share classes are excluded, while closed (“dead”) funds are retained to avoid survivorship bias. In 2010, the provider began including two time-invariant data fields for the manager’s self-reported minimum and maximum net leverage, respectively. I argue that these leverage ranges represent reasonably exogenous indicators of the manager’s choice of net-leverage mandate. To explore the determinants of these choices, I estimate the following regression:

$$\begin{aligned} MAX\_NET_i = c + MARKET_i + MFEE_i + IFEE_i + \log(REDNOTI_i) \\ + \log(REDFREQ_i) + LOCKUP_i + HWM_i + UCITS_i + \varepsilon_i, \end{aligned} \quad (1.20)$$

where  $MAX\_NET$  represents the fund’s self-reported maximum net leverage, and  $c$  is the intercept.  $MARKET$  refers to the average monthly market excess return ( $RMRF$ ) in the year prior to the fund’s inception (or the three years prior, depending on the regression specification). I also include the subsequent average market return to control for the possibility that managers are successful market timers who choose a higher-net mandate in anticipation of future market outperformance.  $MFEE$  and  $IFEE$  denote the fund’s management and incentive fees, respectively, as a percentage per annum.  $REDNOTI$  and  $REDFREQ$  are the redemption notice period and the frequency of redemption dates, respectively, both measured in days. For example, a fund that allows redemptions on a monthly basis with a 30-day notice period would have both  $REDNOTI$  and  $REDFREQ$  set to 30.  $LOCKUP$ ,  $HWM$ , and  $UCITS$  are indicator variables set to 1 if the fund has a lockup provision, subjects its incentive fees to a high-water mark provision, or complies with the EU’s UCITS directive, respectively, and 0 otherwise.

The regression results, reported in Columns (1) and (2) of Table 1.9, suggest that L/S equity hedge funds are launched with more aggressive net-leverage limits when recent market performance has been strong. Specifically, a 1-percentage-point increase in the average monthly market return ( $MARKET$ ) over the prior year (or prior three years) is associated with a 2.09% (4.81%) higher net-leverage limit.<sup>20</sup>

**Underlying causes** I hypothesize that net-leverage mandates are strategically chosen to cater to investor preferences. Labels such as “market neutral” or “long biased” signal to prospective investors the expected market exposure of the fund. As naïve extrapolators, investors’ “appetite for beta” may be influenced by recent market performance, which, in turn, incentivizes fund managers to launch funds with higher net-leverage mandates following strong market returns.

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<sup>20</sup>The fund inception dates range from September 1969 to January 2023. Managers may report their leverage ranges to EurekaHedge only after a fund has been launched (1), or they might change the reported ranges over time (2). In these cases, the reported leverage levels become endogenous and might no longer reflect the manager’s initial choice of leverage. However, changes in reported leverage ranges have been found to be very rare (Liang & Qiu, 2019), which alleviates concerns over problem (2). Regarding (1), I conduct robustness tests using only funds that were launched after 2009 – to account for the fact that leverage ranges became available only in 2010 – and were added to the database within three years of launch. The results, unreported, are qualitatively identical.

To investigate, I first obtain representations of net-leverage mandates that are, arguably, accessible to investors. Specifically, I search the funds’ strategy descriptions for the terms “long bias”, “long only”, “low net”, “market neutral”, “short bias”, and “short only” to identify the net-leverage mandate communicated to investors. Given that “the vast majority of strategy descriptions remain unchanged over time” (Joenväärä et al., 2019, page 3), I once again argue that these descriptions are largely exogenous.<sup>21</sup> Over 80% of funds with matches for the aforementioned terms self-describe as “long bias” or “market neutral”. Therefore, I categorize the funds into two groups: those with matches for “long bias” or “long only” are classified as “high-net” funds, while those with matches for “market neutral”, “short bias”, or “low net” are classified as “low-net” funds. (There were no matches for “short only” funds.) This classification naturally aligns with the self-reported minimum and maximum net leverage levels: of the 387 funds for which both a maximum net leverage and this “high-net” or “low-net” classification are available, the “high-net” funds have an average maximum net leverage of 95.2%, while the average for the “low-net” funds is 39.3%. The  $t$ -statistic for the difference in means is  $t = 13.84$ . The differences for average minimum net leverage are similar (325 overlapping funds, “high-net”: 24.6%, “low-net”:  $-10.9\%$ ,  $t = 6.91$ ). Naturally, “high-net” funds have a much higher average market beta (of 0.64) than “low-net” funds (0.11,  $t = 19.44$ ).

In Columns (5) and (6), I estimate binary logit regressions predicting whether a fund is “high-net” or not (“low-net”). Consistent with the results in Columns (1) to (4), Equity L/S hedge funds are more likely to have a “high-net” mandate if their launches follow periods of stronger market returns. To test whether funds benefit from choosing “high-net” mandates in this manner, I estimate regressions on fund size at inception (*START\_AUM*) in Columns (7) to (10) (similar to Lu et al., 2022, Table 2).<sup>22</sup> The variable of interest is the interaction between *MARKET* and *HIGH\_NET*, where *HIGH\_NET* is an indicator variable equal to 1 for “high-net” funds, and 0 for “low-net” funds. The positive coefficients for this interaction imply that “high-net” funds raise more capital at fund launch if market performance has been better. Specifically, in Column (7), given the average inception size is USD 32.11 million, the coefficient for the interaction term (0.33) implies that “high-net” funds start with USD 12.69 million more capital if monthly market excess returns have been 1% higher in the past three years. When regressing on AUM (without taking the logarithm) in Column (10), I obtain an economically similar effect of USD 12.16 million in additional capital. The interactions with the prior-year market returns in Columns (7) and (9) are positive but statistically insignificant.

## 1.8 Conclusion

I analyze new data on hedge fund leverage. The dataset consists of 25,119 month-end leverage observations for 432 L/S equity hedge funds between 2000 and 2022. For the L/S equity strategy, leverage levels are particularly informative about risk exposures. Specifically, net leverage – long minus short leverage – provides a more accurate measure of current market-risk exposure than estimated betas. Since the net

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<sup>21</sup>In particular, I search the data fields “Strategy” and “Secondary Investment Strategy”, where “Strategy” is a longer, narrative summary of the investment approach, while “Secondary Investment Strategy” is a concise description, with the most frequent values being “Long Bias” and “Market Neutral”. I give preference to the “Secondary Investment Strategy” data field, using the “Strategy” field only if the former is inconclusive.

<sup>22</sup>Identifying the *START\_AUM* is not trivial, because AUM data immediately after fund inception is often missing or unrealistically low. I define *START\_AUM* as the earliest AUM observation of the fund above USD 1 million within twelve months of inception.

leverage of a L/S equity hedge fund reflects the level of market risk currently desired by the fund manager, net-leverage data are valuable for studying managerial decision-making.

Net leverage exhibits significant dispersion within funds, and the monthly dynamics of net leverage are economically relevant to fund performance. Funds that successfully manage their net-leverage levels significantly outperform their peers. However, I find no evidence of market-timing skill among the sampled funds: neither is the percentage of skillful market timers significant nor are net-leverage changes informative about future market conditions.

Instead, my main finding is the stylized fact that fund managers allow leverage to drift in response to two largely external factors: (1) investor capital flows and (2) changes in the prices of securities held in the portfolio. As investors contribute or redeem capital and as portfolio securities are marked to market, leverage changes. These leverage drifts provide a link between the low turnover of L/S equity hedge fund portfolios (Brunnermeier & Nagel, 2004; Griffin & Xu, 2009) and the procyclicality of L/S equity hedge fund market betas (Fung & Hsieh, 2004a, 2011). Managers who allow net leverage to drift expose their fund returns to equity indices' time-series momentum in the sense of Moskowitz et al. (2012). Such exposures were documented by Ardia et al. (2024) and Chevalier and Darolles (2019).

Finally, while net leverage does fluctuate to an economically significant extent, it is usually managed toward a target. I find that the choice of net-leverage mandate at fund inception is positively associated with recent market performance: managers tend to choose a more aggressive mandate (and therefore a higher beta) if the market has recently performed well, potentially in an effort to exploit investors' tendency to extrapolate past returns into the future. Consistent with this idea, I observe that funds with a higher net-leverage mandate raise more capital at inception when markets have performed better.

While this chapter focused on net leverage, future research could further explore the role of gross leverage. Similar to net-leverage levels, gross-leverage levels could be used to measure spread-risk exposures, assess factor-timing ability, study risk-shifting behaviors, and evaluate the potentially endogenous relationship between hedge fund leverage and macroeconomic variables. Additionally, hedge fund leverage levels allow for return decompositions and attribution analyses. This chapter followed Lo (2008) in differentiating between returns from "active" and "passive" market allocations. It would also be possible to isolate security-selection returns or estimate the relative magnitude of long- versus short-book returns through cross-sectional regressions.

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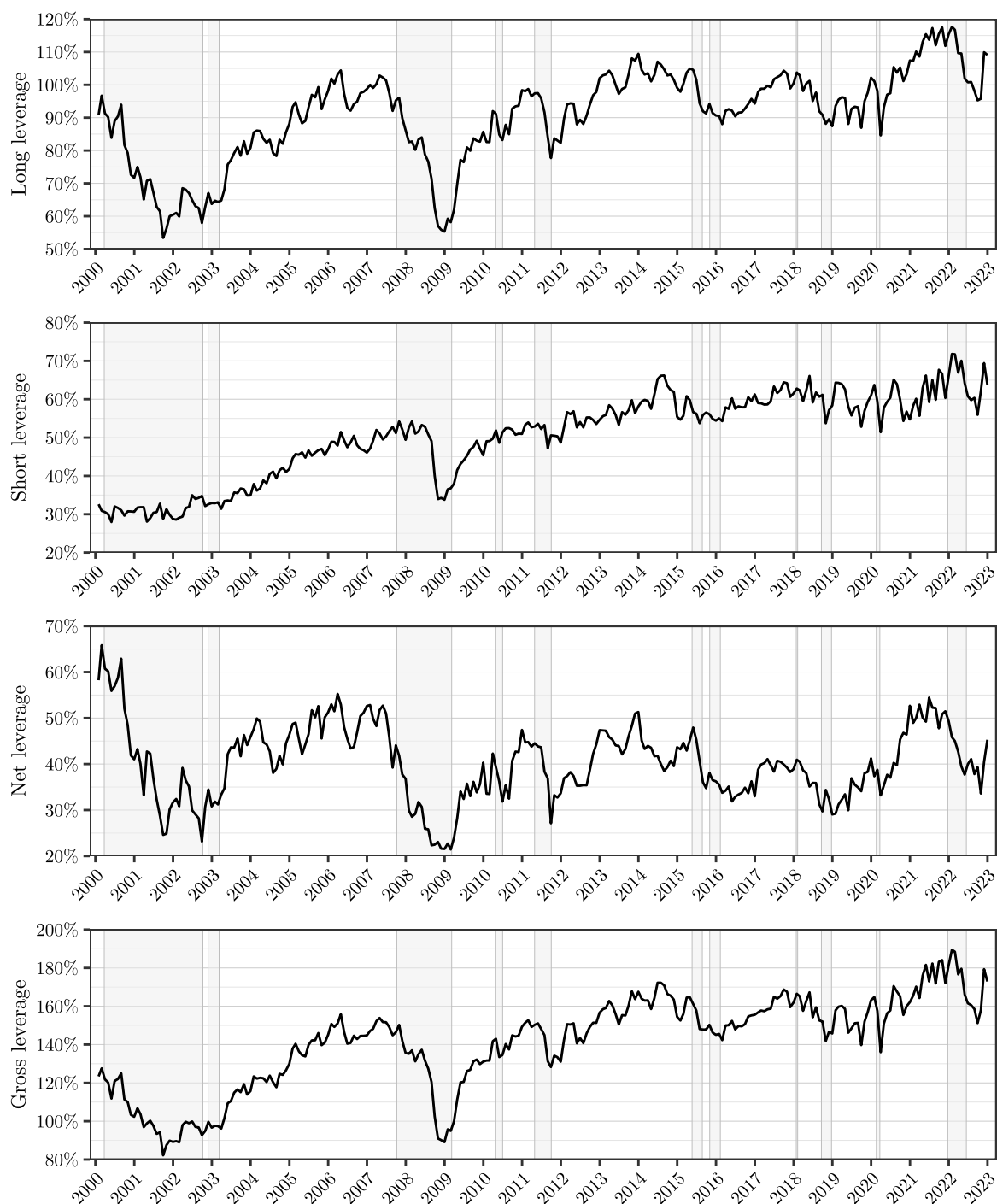
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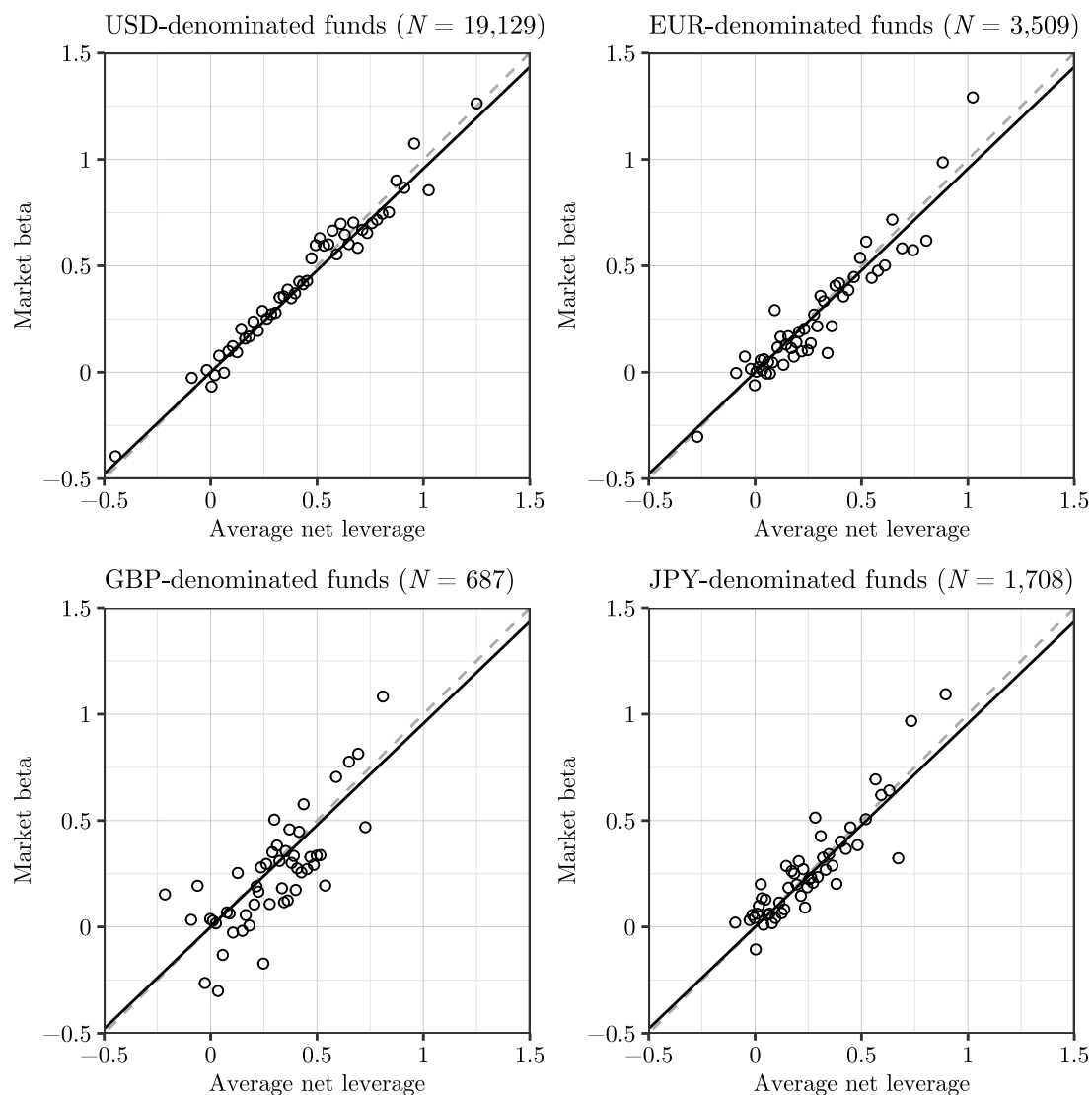
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## Figures

**Figure 1.1:** Leverage levels of long/short equity hedge funds



*Note.* The figure shows time series of hedge fund leverage levels, averaged across all funds in the sample. The sample includes 432 EUR-, GBP-, JPY-, and USD-denominated long/short equity hedge funds between January 2000 and December 2022. Grey areas mark periods when the S&P 500 index declined by 10% or more from its peak to its trough.

**Figure 1.2:** Net leverage versus OLS-estimated betas of long/short equity hedge funds

*Note.* This figure shows binned scatterplots illustrating the relationship between average net leverage and OLS-estimated market betas for long/short (L/S) equity hedge funds. Each plot corresponds to a different fund currency. In the first plot, observations for USD-denominated L/S equity hedge funds are pooled and sorted into 2% quantiles based on net leverage, and a market beta is estimated for each of the 50 resulting groups using a CAPM model without additional factors. The estimated beta of each group is then plotted against its average net leverage. The identity line, shown in grey, represents a one-to-one relationship. The remaining plots apply the same analysis to EUR-, GBP-, and JPY-denominated L/S equity hedge funds.  $N$  denotes the number of observations. The sample includes 432 funds (334 USD-, 59 EUR-, 27 JPY-, and 12 GBP-denominated) and covers January 2000 to December 2022.

## Tables

**Table 1.1:** Summary statistics

*Note.* The table summarizes the sample used in Chapter 1. The sample covers EUR-, GBP-, JPY-, and USD-denominated long/short equity hedge funds between January 2000 and December 2022. Panel A reports descriptive statistics for the main variables. Autocorrelations and standard deviations are the averages of the individual funds' autocorrelations and standard deviations, respectively. The other statistics are calculated across funds. Autocorrelations are calculated using only observations with adjacent months. *LONG*, *SHORT*, *NET*, and *GROSS* are month-end long, short, net, and gross leverage, respectively. *RET* is the fund's monthly net (after-fee) return. *CAPM\_ALPHA* is the monthly CAPM alpha (Lintner, 1965; Sharpe, 1964), *FF5\_ALPHA* is the monthly 5-factor alpha of Fama and French (1993, 2015), and *FH8\_ALPHA* is the monthly 8-factor alpha of Fung and Hsieh (2001). Factor loadings are estimated over rolling 24-month periods. *AUM* are month-end assets under management, in USD million. *FAGE*, fund age, is the number of years since fund inception. Panel B summarizes the availability of leverage observations by calendar year, fund currency, and year of fund launch. Panel C shows correlation coefficients between the four measures of leverage (long, short, gross, and net leverage). Panel D shows two transition matrices for the relative frequency that a fund transitions from one net-leverage bracket to another within one (upper table) or two years (bottom table).

**Panel A:** Distribution of fund characteristics

Variable	<i>N</i> funds	<i>N</i> observ.	% observed	Min.	Median	Mean	Max.	Std. dev.	Auto- correl.
<i>LONG</i>	432	25,119	100.0%	0.0%	88.0%	88.8%	353.7%	19.0%	0.65
<i>SHORT</i>	432	25,119	100.0%	0.0%	42.9%	49.4%	356.5%	14.4%	0.60
<i>NET</i>	432	25,119	100.0%	-191.8%	37.0%	39.4%	174.9%	15.6%	0.57
<i>GROSS</i>	432	25,119	100.0%	0.0%	129.1%	138.2%	710.1%	29.3%	0.64
<i>RET</i>	432	25,103	99.9%	-35.88%	0.72%	0.81%	41.20%	3.33%	0.08
<i>CAPM_ALPHA</i>	404	18,937	75.4%	-24.13%	0.32%	0.42%	34.64%	2.61%	0.01
<i>FF5_ALPHA</i>	404	18,937	75.4%	-17.53%	0.31%	0.41%	26.77%	2.20%	0.00
<i>FH8_ALPHA</i>	404	18,937	75.4%	-13.30%	0.31%	0.38%	25.06%	2.03%	0.00
<i>AUM</i>	408	21,019	83.7%	0.10	145.61	347.89	5,962.28	140.25	0.82
<i>FAGE</i>	432	25,119	100.0%	0.00	4.25	5.40	34.19	1.60	0.87

**Panel B:** Number of leverage observations by year, fund currency, and fund launch year

	Number of funds	Number of observations for <i>LONG</i> and <i>SHORT</i> (each)				
		Total	Minimum per fund	Median per fund	Mean per fund	Maximum per fund
<i>By year</i>						
2000	35	309	1	12.0	8.83	12
2001	71	638	1	12.0	8.99	12
2002	93	930	1	12.0	10.00	12
2003	101	997	2	12.0	9.87	12
2004	131	1,261	1	12.0	9.63	12
2005	159	1,500	1	12.0	9.43	12
2006	169	1,679	1	12.0	9.93	12
2007	201	1,887	1	12.0	9.39	12
2008	216	2,164	1	12.0	10.02	12
2009	194	1,864	1	12.0	9.61	12
2010	190	1,808	1	12.0	9.52	12
2011	153	1,486	1	12.0	9.71	12
2012	145	1,437	1	12.0	9.91	12
2013	143	1,358	1	12.0	9.50	12
2014	115	877	1	8.0	7.63	12
2015	121	1,047	1	10.0	8.65	12
2016	111	1,008	1	11.0	9.08	12
2017	98	883	1	10.5	9.01	12
2018	72	681	1	11.0	9.46	12
2019	55	523	1	11.0	9.51	12
2020	45	375	1	9.0	8.33	12
2021	30	250	1	10.0	8.33	12
2022	16	157	2	10.5	9.81	12
<i>By fund currency</i>						
EUR	59	3,524	11	50.0	59.73	165
GBP	12	690	12	40.5	57.50	200
JPY	27	1,712	12	40.0	63.41	163
USD	334	19,193	10	42.0	57.46	256
<i>By year of fund inception</i>						
1950 to 1994	13	674	14	44.0	51.85	129
1995 to 1999	37	2,359	10	40.0	63.76	168
2000 to 2004	150	10,604	11	56.5	70.69	256
2005 to 2009	149	7,943	10	39.0	53.31	189
2010 to 2014	62	2,711	13	39.5	43.73	122
2015 to 2022	21	828	10	35.0	39.43	77
All funds	432	25,119	10	43.0	58.15	256

**Panel C:** Correlations between changes and levels of long, short, gross, and net leverage

Leverage changes				
	$\Delta LONG$	$\Delta SHORT$	$\Delta NET$	$\Delta GROSS$
$\Delta LONG$	1			
$\Delta SHORT$	0.43	1		
$\Delta NET$	0.61	-0.45	1	
$\Delta GROSS$	0.87	0.83	0.13	1

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Leverage levels				
	$LONG$	$SHORT$	$NET$	$GROSS$
$LONG$	1			
$SHORT$	0.60	1		
$NET$	0.45	-0.44	1	
$GROSS$	0.90	0.89	0.01	1

**Panel D:** Transition matrices for net leverage

Year $t$	Year $t + 1$										N/A	$N$
	1	2	3	4	5	6	7	8	9			
1: $NET \leq 0\%$	36%	18%	10%	13%	8%	0%	5%	0%	0%	10%	39	
2: $0\% < NET \leq 10\%$	13%	27%	13%	17%	9%	4%	4%	3%	4%	6%	70	
3: $10\% < NET \leq 20\%$	10%	18%	22%	12%	12%	4%	4%	4%	2%	14%	51	
4: $20\% < NET \leq 30\%$	5%	14%	14%	21%	12%	12%	2%	11%	0%	9%	57	
5: $30\% < NET \leq 40\%$	2%	4%	8%	12%	22%	14%	10%	8%	0%	20%	50	
6: $40\% < NET \leq 50\%$	5%	2%	12%	2%	20%	15%	15%	12%	7%	10%	41	
7: $50\% < NET \leq 60\%$	0%	0%	0%	3%	13%	10%	13%	20%	23%	17%	30	
8: $60\% < NET \leq 80\%$	4%	0%	0%	4%	4%	11%	16%	25%	20%	16%	55	
9: $NET > 80\%$	0%	8%	3%	3%	8%	3%	8%	21%	36%	13%	39	

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Year $t$	Year $t + 2$										N/A	$N$
	1	2	3	4	5	6	7	8	9			
1: $NET \leq 0\%$	31%	18%	5%	10%	3%	5%	3%	10%	0%	15%	39	
2: $0\% < NET \leq 10\%$	4%	29%	14%	6%	3%	6%	1%	6%	6%	26%	70	
3: $10\% < NET \leq 20\%$	4%	20%	12%	20%	8%	4%	6%	2%	2%	24%	51	
4: $20\% < NET \leq 30\%$	4%	4%	4%	18%	18%	7%	16%	2%	4%	26%	57	
5: $30\% < NET \leq 40\%$	4%	4%	6%	6%	14%	14%	4%	10%	8%	30%	50	
6: $40\% < NET \leq 50\%$	5%	2%	5%	5%	12%	7%	7%	5%	24%	27%	41	
7: $50\% < NET \leq 60\%$	0%	0%	10%	17%	0%	10%	0%	10%	13%	40%	30	
8: $60\% < NET \leq 80\%$	0%	2%	2%	5%	7%	7%	9%	25%	15%	27%	55	
9: $NET > 80\%$	3%	3%	3%	5%	5%	5%	3%	21%	31%	23%	39	

**Table 1.2:** Determinants of fund return

*Note.* This table reports results from multivariate regressions on monthly fund returns in excess of the risk-free rate ( $RET - RF$ ). The independent variables are the five factors of Fama and French (2015) ( $RMRF$ ,  $SMB$ ,  $HML$ ,  $RMW$ , and  $CMA$ ) and the momentum factor of Carhart (1997) ( $UMD$ ). Each of these factors is interacted with net or short leverage at prior month-end ( $NET$  and  $SHORT$ , respectively). \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% confidence level, respectively. Standard errors are clustered by fund and year-month;  $t$ -statistics are shown in parentheses,  $\chi^2$ -statistics in brackets. All regressions include fixed effects (FE) for fund and year-month. The sample covers EUR-, GBP-, JPY-, and USD-denominated L/S equity hedge funds between January 2000 and December 2022.

Dependent variable:	$RET - RF$			
	(1)	(2)	(3)	(4)
$NET \times RMRF$ (I)	0.977*** (16.334)	0.984*** (17.056)	0.899*** (18.750)	0.903*** (19.096)
$NET \times SMB$		0.280*** (4.344)	0.354*** (4.798)	0.342*** (4.588)
$NET \times HML$		-0.258*** (-3.149)	0.104 (0.991)	0.118 (1.080)
$NET \times RMW$			0.028 (0.284)	0.010 (0.107)
$NET \times CMA$			-0.616*** (-5.126)	-0.638*** (-4.943)
$NET \times UMD$				0.039 (0.876)
$SHORT \times RMRF$	0.014 (0.519)	0.027 (0.894)	0.017 (0.616)	0.021 (0.792)
$SHORT \times SMB$		0.044 (0.863)	0.090 (1.270)	0.067 (0.996)
$SHORT \times HML$		-0.094* (-1.728)	0.010 (0.166)	0.041 (0.814)
$SHORT \times RMW$			0.057 (0.972)	0.015 (0.208)
$SHORT \times CMA$			-0.163* (-1.787)	-0.201** (-2.338)
$SHORT \times UMD$				0.073* (1.885)
Difference: (I) - 1	-0.023	-0.016	-0.101***	-0.097***
$\chi^2$ -statistic	[0.36]	[0.16]	[7.40]	[7.11]
FE (fund, year-month)	Yes	Yes	Yes	Yes
Observations	23,629	23,629	23,629	23,629
Adjusted R <sup>2</sup>	0.387	0.391	0.397	0.397
Within adj. R <sup>2</sup>	0.202	0.207	0.214	0.215

**Table 1.3:** Tactical versus passive market exposure

*Note.* The table compares the explanatory power of (A) OLS-estimated betas, (B) month-end net leverage, and (C) fund-average net leverage, as competing measures of market exposure. Diebold-Mariano (DM) statistics are shown in brackets. The DM-statistic is compared with a Student's  $t$ -distribution with  $k - 1$  degrees of freedom (where  $k$  is the number of observations), as suggested by Harvey et al. (1997). The table reports also the  $R^2$  of the three methods. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% confidence level, respectively. The sample covers EUR-, GBP-, JPY-, and USD-denominated L/S equity hedge funds between January 2000 and December 2022.

Volatility of $NET$ (quartile)	Beta estimated over 12 months				
	Any	Q1	Q2	Q3	Q4
(A) RMSE for Beta	3.16%	2.62%	2.85%	3.12%	3.89%
(B) RMSE for $NET$	2.99%	2.57%	2.80%	3.02%	3.49%
(C) RMSE for $\overline{NET}$	3.18%	2.60%	2.89%	3.21%	3.87%
(A) – (B)	0.17%***	0.05%	0.05%	0.10%**	0.40%***
[Diebold-Mariano statistic]	[7.53]	[1.62]	[1.49]	[2.47]	[7.10]
(A) – (C)	–0.02%	0.02%	–0.04%	–0.09%**	0.02%
[Diebold-Mariano statistic]	[–0.98]	[0.59]	[–1.21]	[–2.03]	[0.36]
(B) – (C)	–0.19%***	–0.03%**	–0.09%***	–0.19%***	–0.38%***
[Diebold-Mariano statistic]	[–12.77]	[–2.56]	[–4.84]	[–7.16]	[–9.37]
$R^2$ for Beta	27.07%	27.18%	34.03%	34.74%	15.69%
$R^2$ for $NET$	34.64%	29.94%	36.33%	38.88%	32.27%
$R^2$ for $\overline{NET}$	26.07%	28.23%	32.16%	30.97%	16.51%
Number of observations	16,907	4,227	4,227	4,226	4,227
Volatility of $NET$ (quartile)	Beta estimated over 24 months				
	Any	Q1	Q2	Q3	Q4
(A) RMSE for Beta	3.10%	2.56%	2.92%	3.06%	3.73%
(B) RMSE for $NET$	2.94%	2.53%	2.88%	2.95%	3.34%
(C) RMSE for $\overline{NET}$	3.13%	2.56%	2.94%	3.11%	3.80%
(A) – (B)	0.16%***	0.03%	0.04%	0.10%**	0.40%***
[Diebold-Mariano statistic]	[6.90]	[0.87]	[1.02]	[2.46]	[7.05]
(A) – (C)	–0.04%	0.00%	–0.02%	–0.05%	–0.07%
[Diebold-Mariano statistic]	[–1.64]	[0.08]	[–0.45]	[–1.18]	[–1.31]
(B) – (C)	–0.19%***	–0.03%**	–0.06%***	–0.15%***	–0.46%***
[Diebold-Mariano statistic]	[–10.74]	[–2.25]	[–2.92]	[–5.02]	[–8.87]
$R^2$ for Beta	31.12%	36.42%	35.66%	35.18%	20.98%
$R^2$ for $NET$	37.98%	37.95%	37.37%	39.52%	36.92%
$R^2$ for $\overline{NET}$	29.52%	36.57%	34.95%	33.03%	18.15%
Number of observations	12,760	3,190	3,190	3,190	3,190

**Table 1.4:** Economic relevance of net-leverage changes

*Note.* The table provides evidence that changes in market-risk exposure (proxied by net leverage) impact fund performance. All funds with at least 20 net-leverage observations (365 out of 432) are grouped into quintiles based on their market-timing ability. Market-timing ability is calculated as the covariance of market-risk exposure, proxied by net leverage at prior month-end (*NET*), with the current-month market excess return (*RMRF*). Average net returns (*RET*), CAPM alphas (Lintner, 1965; Sharpe, 1964) (*CAPM\_ALPHA*), 5-factor Fama and French (1993, 2015) alphas (*FF5\_ALPHA*), and 8-factor Fung and Hsieh (2001) alphas (*FH8\_ALPHA*) are compared across quintiles. The *t*-statistics for the differences in means between the first and fifth quintile are shown in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% confidence level, respectively. The sample covers EUR-, GBP-, JPY-, and USD-denominated L/S equity hedge funds between January 2000 and December 2022.

Dependent variable:	<i>TIMING_ABILITY</i> (quintile)					Q5–Q1
	Q1	Q2	Q3	Q4	Q5	
<i>TIMING_ABILITY</i>	−0.14%	−0.03%	0.01%	0.07%	0.28%	***0.42% (19.30)
<i>RET</i>	0.57%	0.79%	0.78%	0.88%	1.03%	***0.46% (3.10)
<i>CAPM_ALPHA</i>	0.31%	0.43%	0.47%	0.51%	0.80%	***0.49% (3.96)
<i>FF5_ALPHA</i>	0.39%	0.44%	0.46%	0.42%	0.66%	*0.27% (1.95)
<i>FH8_ALPHA</i>	0.30%	0.41%	0.46%	0.42%	0.58%	**0.29% (2.19)
Number of funds	73	73	73	73	73	

**Table 1.5:** Descriptive statistics of leverage determinants

*Note.* The table describes the leverage determinants considered in Chapter 1. Panel A reports summary statistics for these determinants. For all fund-specific determinants, autocorrelations and standard deviations are the averages of the individual funds' autocorrelations and standard deviations, respectively. The other statistics are calculated across funds. Autocorrelations are calculated using only observations with adjacent months. Panels B and C report correlation coefficients among the fund-specific and macro leverage determinants, respectively. The variables are defined as follows:

- Main variables: *DRIFT* is the estimated monthly change in net leverage due to mark-to-market effects and investor flows. *NET* (lagged) is net leverage at the prior month-end.  $|RET|$  is the absolute monthly fund return.
- Fund-specific leverage supply: *RET12* is the cumulative fund return over the twelve months prior, including the current month. *VOL12* is the standard deviation of those returns over the same period.  $\log(AUM)$  is the logarithm of month-end fund assets under management, in USD million. *FLOW1* and *FLOW3* are fund flows in the current month ( $t$ ) and over the period  $t - 2$  to  $t$ , respectively.
- Risk-shifting: *DIST2HWM* is the distance of the fund's NAV from its high-water mark (Buraschi et al., 2014), lagged by one month.
- Market timing:  $\Delta VIX$  is the change in the CBOE VIX level (month-end to month-end). *RMRF* is the Fama and French (1993) market excess return.  $\Delta LIQ$  is the change in the Pástor and Stambaugh (2003) aggregate liquidity measure.
- Macro determinants: Following Ang et al. (2011), these variables include *IB\_CDS* (the month-end market-capitalization-weighted average CDS premium on 10-year senior bonds of leading investment banks: Barclays, Bear Stearns, BNP Paribas, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, J.P. Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, and UBS); *IB\_RET* (the market-capitalization-weighted average stock return of the banks listed above); *SPX* (S&P 500 index monthly total return); *VIX* (month-end CBOE VIX level); *LIBOR* (month-end 3-month LIBOR, based on USD); *TED* (the difference between the 3-month US Treasury bill rate and the 3-month LIBOR, based on USD); *TERM* (the spread between the 10-year US Treasury note rate and the 3-month US Treasury bill rate); and *AGGFLOW* (aggregate hedge-fund industry flows in the three months prior, calculated as in Ang et al. (2011):  $AGGFLOW_t = IAUM_{i,t}/IAUM_{i,t-3} - (1 + R_{b,t-2})(1 + R_{b,t-1})(1 + R_{b,t})$ , where  $IAUM_t$  are the hedge-fund industry AUM at month-end  $t$ , interpolated from quarterly data obtained from BarclayHedge.  $R_{b,t}$  is the return of the "Barclay Hedge Fund Index" in month  $t$ ).

**Panel A:** Summary statistics of leverage determinants

	Min.	Median	Mean	Max.	Std. dev.	Auto-cor.	% observed
<i>Main variables</i>							
<i>DRIFT</i>	-21.13%	0.01%	-0.25%	20.69%	4.00%	0.066	76.24%
<i>NET</i> (lagged)	-191.79%	37.00%	39.47%	174.93%	15.26%	0.545	94.07%
$ RET $	0.00%	1.77%	2.61%	41.20%	2.27%	0.100	99.94%
<i>Fund-specific leverage supply</i>							
<i>RET12</i>	-68.71%	9.20%	11.12%	300.44%	12.74%	0.766	88.67%
<i>VOL12</i>	0.30%	2.57%	3.08%	18.46%	0.97%	0.770	88.67%
$\log(AUM)$	0.097	4.970	4.874	8.693	0.612	0.825	90.34%
<i>FLOW1</i>	-38.45%	0.23%	1.99%	67.49%	10.05%	0.117	79.70%
<i>FLOW3</i>	-63.03%	1.29%	7.14%	172.17%	23.81%	0.616	76.83%
<i>Risk-shifting</i>							
<i>DIST2HWM</i>	-100.00%	12.88%	14.98%	122.62%	8.24%	0.781	89.18%
<i>Market timing</i>							
$\Delta VIX$	-19.39%	-0.37%	-0.01%	21.27%	4.74%	-0.075	100.00%
<i>RMRF</i>	-19.77%	1.04%	0.42%	13.88%	4.56%	0.101	100.00%
$\Delta LIQ$	-38.12%	0.35%	0.03%	32.89%	9.71%	-0.548	100.00%
<i>Macro determinants (Ang et al., 2011)</i>							
<i>IB_CDS</i>	0.18%	1.03%	0.98%	2.43%	0.49%	0.943	90.02%
<i>IB_RET</i>	-27.82%	0.78%	0.03%	25.98%	7.41%	0.107	100.00%
<i>SPX</i>	-16.80%	1.24%	0.57%	12.82%	4.47%	0.020	100.00%
<i>VIX</i>	9.51%	17.83%	20.33%	59.89%	8.14%	0.801	100.00%
<i>LIBOR</i>	0.12%	1.19%	1.94%	6.86%	1.88%	0.979	100.00%
<i>TED</i>	0.06%	0.31%	0.48%	3.15%	0.38%	0.825	100.00%
<i>TERM</i>	-0.77%	2.04%	1.84%	3.79%	1.15%	0.952	100.00%
<i>AGGFLOW</i>	-20.10%	1.77%	1.57%	13.87%	4.89%	0.945	99.47%

**Panel B:** Correlations among fund-specific leverage determinants

	<i>DRIFT</i>	<i>NET</i> (lagged)	$ RET $	<i>RET12</i>	<i>VOL12</i>	$\log(AUM)$	<i>FLOW1</i>	<i>FLOW3</i>	<i>DIST2HWM</i>	$\Delta VIX$	<i>RMRF</i>	$\Delta LIQ$
<i>DRIFT</i>	1											
<i>NET</i> (lagged)	-0.08	1										
$ RET $	0.05	0.27	1									
<i>RET12</i>	-0.12	0.22	0.07	1								
<i>VOL12</i>	0.05	0.35	0.53	0.07	1							
$\log(AUM)$	0.00	0.02	-0.03	0.01	-0.07	1						
<i>FLOW1</i>	-0.65	0.03	-0.03	0.23	-0.08	-0.02	1					
<i>FLOW3</i>	-0.44	0.01	-0.06	0.27	-0.11	-0.02	0.67	1				
<i>DIST2HWM</i>	-0.05	0.22	0.03	0.44	0.03	0.23	0.04	-0.01	1			
$\Delta VIX$	-0.12	0.02	0.06	-0.01	-0.02	0.02	0.01	0.02	0.06	1		
<i>RMRF</i>	0.12	0.04	-0.02	0.10	-0.02	-0.01	0.03	0.01	0.00	-0.73	1	
$\Delta LIQ$	0.06	-0.01	-0.03	0.00	0.01	-0.01	-0.01	-0.01	-0.02	-0.10	0.12	1

**Panel C:** Correlations among macro leverage determinants

	<i>IB_CDS</i>	<i>IB_RET</i>	<i>SPX</i>	<i>VIX</i>	<i>LIBOR</i>	<i>TED</i>	<i>TERM</i>	<i>AGGFLOW</i>
<i>IB_CDS</i>	1							
<i>IB_RET</i>	-0.15	1						
<i>SPX</i>	-0.13	0.79	1					
<i>VIX</i>	0.41	-0.41	-0.44	1				
<i>LIBOR</i>	-0.56	-0.06	-0.12	-0.14	1			
<i>TED</i>	0.10	-0.28	-0.33	0.46	0.45	1		
<i>TERM</i>	0.36	-0.02	0.00	0.21	-0.62	-0.02	1	
<i>AGGFLOW</i>	-0.47	0.00	0.07	-0.48	0.08	-0.33	-0.06	1

**Table 1.6:** Determinants of net-leverage changes

*Note.* The table examines determinants of changes in net leverage ( $\Delta NET$ ) using linear regression. The key independent variable, *DRIFT*, is the expected change in net leverage due to flows and mark-to-market effects. The other variables are defined in Table 1.5. Standard errors are clustered by fund and year-month. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% confidence level, respectively. The sample covers EUR-, GBP-, JPY-, and USD-denominated L/S equity hedge funds between January 2000 and December 2022.

**Panel A:** Fund-specific leverage determinants

	Dependent variable: $\Delta NET$					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>DRIFT</i>	0.207*** (4.062)	0.296*** (3.528)	0.276*** (5.302)	0.186*** (3.573)	0.179*** (3.605)	0.153*** (3.184)
<i>RET12</i>		0.043*** (3.956)				
<i>VOL12</i>		-0.250* (-1.854)				
$\log(AUM)$		-0.003 (-1.113)				
<i>FLOW1</i>		0.063** (2.417)				
<i>FLOW3</i>		-0.015** (-2.071)				
<i>DIST2HWM</i> ( $\geq 0$ )			-0.062*** (-4.980)	0.015 (0.897)		
<i>DIST2HWM</i> (< 0)			0.058** (2.084)	0.028 (0.710)		
$\Delta VIX$			-0.229*** (-4.147)	-0.216*** (-4.680)	-0.210*** (-4.548)	
$\Delta VIX (t + 1)$					0.072 (1.389)	
<i>RMRF</i>						0.388*** (7.169)
<i>RMRF (t + 1)</i>						0.008 (0.205)
$\Delta LIQ$						0.017 (0.766)
$\Delta LIQ (t + 1)$						0.009 (0.400)
<i>NET (t - 1)</i>	-0.224*** (-8.286)	-0.224*** (-7.766)		-0.225*** (-8.021)	-0.223*** (-8.274)	-0.229*** (-8.441)
$ RET $	0.141** (2.077)	0.160** (2.248)	-0.049 (-0.753)	0.175** (2.587)	0.169** (2.589)	0.163** (2.397)
FE (fund)	Yes	Yes	Yes	Yes	Yes	Yes
FE (year-month)	No	No	No	No	No	No
Observations	19,151	16,882	18,594	18,594	19,151	19,151
Adjusted $R^2$	0.105	0.104	0.005	0.113	0.112	0.125
Within adj. $R^2$	0.119	0.119	0.019	0.126	0.125	0.138
Start	2000-01	2000-01	2000-01	2000-01	2000-01	2000-01
End	2022-12	2022-12	2022-12	2022-12	2022-12	2022-12

Panel B: Macro determinants (Ang et al., 2011)

	Dependent variable: $\Delta NET$					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>DRIFT</i>	0.187*** (3.586)	0.180*** (3.727)	0.204*** (4.081)	0.219*** (4.314)	0.175*** (3.351)	0.167*** (3.486)
<i>IB_CDS</i>	-2.488*** (-5.992)				-2.372*** (-3.628)	
<i>IB_RET</i>	0.161*** (5.765)				0.050 (1.465)	
<i>SPX</i>		0.269*** (5.075)			0.137* (1.807)	
<i>VIX</i>		-0.133*** (-4.783)			-0.081** (-2.329)	
<i>LIBOR</i>			-2.363*** (-4.970)		-0.534 (-0.690)	
<i>TED</i>			-0.544*** (-3.130)		-0.202 (-0.681)	
<i>TERM</i>				0.106 (0.784)	-0.249 (-0.823)	
<i>AGGFLOW</i>				0.083** (2.240)	-0.069* (-1.671)	
<i>NET</i> ( $t - 1$ )	-0.249*** (-8.022)	-0.240*** (-8.673)	-0.236*** (-8.637)	-0.228*** (-8.307)	-0.256*** (-8.313)	-0.249*** (-8.689)
$ RET $	0.171** (2.519)	0.251*** (3.723)	0.235*** (3.417)	0.151** (2.209)	0.245*** (3.647)	0.219*** (3.436)
FE (fund)	Yes	Yes	Yes	Yes	Yes	Yes
FE (year-month)	No	No	No	No	No	Yes
Observations	17,397	19,151	19,151	19,059	17,397	19,151
Adjusted $R^2$	0.127	0.127	0.112	0.107	0.130	0.143
Within adj. $R^2$	0.140	0.139	0.125	0.120	0.144	0.128
Start	2003-09	2000-01	2000-01	2000-06	2003-09	2000-01
End	2022-12	2022-12	2022-12	2022-12	2022-12	2022-12

**Table 1.7:** Determinants of net-leverage changes – robustness tests

*Note.* The table presents the results of robustness tests for the regression analysis conducted in Table 1.6. To address three potential concerns, the tests examine whether the results in Table 1.6 are caused by the relationship between leverage drifts and (a) lagged leverage (Columns 1, 5, and 9), (b) fund returns (Columns 2, 3, 6, 7, 10, and 11), or (c) market returns (Columns 4, 8, and 12). Columns 1 to 4 analyze drifts in net leverage (*DRIFT*), Columns 5 to 8 analyze drifts in long leverage (*DRIFT\_L*), and Columns 9 to 12 analyze drifts in short leverage (*DRIFT\_S*). The dependent variables are changes in net, long, or short leverage ( $\Delta NET$ ,  $\Delta LONG$ , and  $\Delta SHORT$ , respectively). All regressions include fixed effects (FE) for fund and year-month, and control for lagged net leverage ( $NET$  ( $t - 1$ )) and absolute fund returns ( $|RET|$ ) (coefficients not reported for presentation purposes). \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively. Standard errors are clustered by fund and year-month;  $t$ -statistics are reported in parentheses. The sample covers EUR-, GBP-, JPY-, and USD-denominated L/S equity hedge funds between January 2000 and December 2022.

	Dependent variable: $\Delta NET$ <i>DRIFT*</i> = <i>DRIFT</i>				Dependent variable: $\Delta LONG$ <i>DRIFT*</i> = <i>DRIFT_L</i>				Dependent variable: $\Delta SHORT$ <i>DRIFT*</i> = <i>DRIFT_S</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(a) Artifact of lagged leverage?												
<i>DRIFT*</i> ( $\geq 0$ )	0.148***				0.124***				0.046			
	(3.340)				(3.632)				(0.775)			
<i>DRIFT*</i> ( $< 0$ )	0.182**				0.179***				0.188***			
	(2.405)				(7.879)				(3.661)			
(b) Artifact of fund return?												
<i>DRIFT*</i> (same sign as <i>RET</i> )		0.211***				0.221***				0.188***		
		(3.025)				(7.889)				(3.622)		
<i>DRIFT*</i> (opp. sign to <i>RET</i> )		0.087*				0.098***				0.094		
		(1.790)				(4.259)				(1.581)		
<i>DRIFT*</i>			0.115**				0.166***				0.130***	
			(2.579)				(8.468)				(3.143)	
<i>RET</i>			0.191***				0.235***				0.033	
			(3.518)				(4.491)				(0.549)	
(c) Artifact of market return?												
<i>DRIFT*</i> (same sign as <i>SPX</i> )				0.200***				0.154***				0.122*
				(4.589)				(6.406)				(1.703)
<i>DRIFT*</i> (opp. sign to <i>SPX</i> )				0.134*				0.154***				0.121***
				(1.766)				(5.152)				(2.818)
FE (fund, year-month)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,151	19,151	19,151	19,151	19,141	19,141	19,141	19,141	19,141	19,141	19,141	19,141
Adjusted $R^2$	0.143	0.143	0.145	0.143	0.153	0.154	0.156	0.153	0.131	0.131	0.130	0.130
Within adj. $R^2$	0.128	0.128	0.130	0.128	0.118	0.119	0.121	0.117	0.131	0.131	0.131	0.131

**Table 1.8:** Exposure to leverage drifts (*DRIFT*) and time-series momentum (*TSMOM*)

*Note.* The table examines the positive relationship between exposure to *DRIFT* and exposure to the time-series momentum of equity indices (*TSMOM\_EQ*). *DRIFT* is the expected change in net leverage due to investor flows and due to marking the fund portfolio to market. First, for each fund, changes in net leverage are regressed on *DRIFT* over rolling 12-, 18-, or 24-month horizons, and the betas recorded. Observations are then sorted into five quintiles (*Low*, *MediumLow*, *Medium*, *MediumHigh*, or *High*) based on the magnitude of the *DRIFT* beta. Next, fund excess returns are regressed on interaction terms between *TSMOM\_EQ* and dummy variables for the *DRIFT* group, where *TSMOM\_EQ* is the monthly excess return of the *TSMOM* factor (Moskowitz et al., 2012) for global equity indices. The remaining independent variables are the five factors of Fama and French (2015) (*RMRF*, *SMB*, *HML*, *RMW*, and *CMA*) and the momentum factor of Carhart (1997) (*UMD*). All regressions include fund fixed effects. Standard errors are clustered by fund and year-month; *t*-statistics are shown in parentheses,  $\chi^2$  statistics in brackets. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% confidence level, respectively. The sample covers EUR-, GBP-, JPY-, and USD-denominated L/S equity hedge funds between January 2000 and December 2022.

	<i>Beta to DRIFT estimated over...</i>		
	<i>...12-month horizons</i>	<i>...18-month horizons</i>	<i>...24-month horizons</i>
(I) <i>TSMOM_EQ</i> × <i>Low</i>	−0.002 (−0.142)	−0.004 (−0.256)	−0.021 (−0.957)
(II) <i>TSMOM_EQ</i> × <i>MediumLow</i>	0.015 (0.877)	0.002 (0.116)	0.032* (1.948)
(III) <i>TSMOM_EQ</i> × <i>Medium</i>	0.035** (2.432)	0.024 (1.471)	0.011 (0.639)
(IV) <i>TSMOM_EQ</i> × <i>MediumHigh</i>	0.035** (2.309)	0.046*** (2.645)	0.045** (2.344)
(V) <i>TSMOM_EQ</i> × <i>High</i>	0.054** (2.571)	0.051** (2.397)	0.051** (2.230)
<i>RMRF</i>	0.333*** (13.117)	0.342*** (12.810)	0.346*** (12.184)
<i>SMB</i>	0.257*** (7.902)	0.268*** (7.920)	0.273*** (7.501)
<i>HML</i>	0.000 (0.010)	0.006 (0.134)	0.004 (0.089)
<i>UMD</i>	0.085*** (3.473)	0.086*** (3.559)	0.080*** (3.270)
<i>RMW</i>	−0.093*** (−3.019)	−0.089*** (−2.898)	−0.090*** (−2.954)
<i>CMA</i>	−0.281*** (−4.115)	−0.304*** (−4.536)	−0.306*** (−4.284)
Difference: (V) − (I)	0.056***	0.055***	0.072***
$\chi^2$ -statistic	[6.72]	[7.66]	[7.96]
FE (fund)	Yes	Yes	Yes
Observations	15,112	13,250	11,610
Adjusted $R^2$	0.230	0.237	0.245
Within adj. $R^2$	0.223	0.234	0.239

**Table 1.9:** Determinants of net-leverage mandates

*Note.* The table reports results from multivariate linear regressions on maximum net leverage (Columns 1 and 2), on the difference between maximum and minimum net leverage (Columns 3 and 4), and on fund AUM at inception (Columns 7 to 10). Maximum and minimum net leverage (*MAX\_NET* and *MIN\_NET*) are the fund's self-reported upper and lower net-leverage limits, while *START\_AUM* is the fund's AUM at inception, in USD million. The table also reports results from binary logit regressions on *HIGH\_NET*, which equals 1 if the fund communicates a “high-net” mandate to its investors, and 0 for a “low-net” mandate (Columns 5 and 6). A fund is classified as “high-net” or “low-net” based on the occurrence of such labels as “long bias”, “market neutral”, or “short bias” in its strategy descriptions. *MARKET* is the average monthly market excess return over the prior or subsequent one- or three-year period. The regressions in Columns (7) to (10) include fixed effects for inception year. All regressions control for the following fund-specific variables (omitted for brevity): *MFEE* and *IFEE* (management and incentive fees, respectively, in percent per annum);  $\log(\text{REDNOTI})$  and  $\log(\text{REDFREQ})$  (redemption notice period and time between redemption dates, respectively, in days); *LOCKUP*, *HWM*, and *UCITS* (indicator variables equal to 1 if the fund has a lockup provision, applies a high-water mark to the incentive fee, or complies with the UCITS directive, respectively). The sample consists of USD-denominated hedge funds in the EurekaHedge database that follow a “Long Short Equities” strategy. Duplicate share classes are excluded, while closed (“dead”) funds are retained to avoid survivorship bias. Standard errors are clustered by inception year, and \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	<i>MAX_NET</i>		<i>MAX_NET</i> – <i>MIN_NET</i>		<i>HIGH_NET</i> (Y/N)		$\log(\text{START\_AUM})$		<i>START_AUM</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>MARKET</i> (prior year)	2.086** (2.261)		2.651** (2.282)		0.101** (2.188)		–0.040 (–0.595)		–5.309** (–2.060)	
<i>MARKET</i> (prior 3 yrs)		4.812** (2.533)		7.622*** (3.083)		0.168* (1.924)		0.021 (0.101)		–3.410 (–0.462)
<i>MARKET</i> (next year)	1.317 (1.490)		0.510 (0.443)		–0.034 (–0.749)		–0.116** (–2.203)		–4.474** (–2.310)	
<i>MARKET</i> (next 3 yrs)		0.899 (0.392)		–1.114 (–0.408)		0.063 (0.677)		–0.038 (–0.194)		5.082 (0.664)
<i>HIGH_NET</i> × <i>MARKET</i> (prior year)							0.029 (0.395)		4.025 (1.646)	
<i>HIGH_NET</i> × <i>MARKET</i> (prior 3 yrs)								0.333*** (2.754)		12.155** (2.021)
<i>HIGH_NET</i>							–0.212* (–1.815)	–0.364*** (–2.956)	–6.155 (–1.412)	–10.537** (–2.167)
Family	OLS	OLS	OLS	OLS	Logit	Logit	OLS	OLS	OLS	OLS
Observations	843	840	622	621	897	892	581	578	581	578
Adj. $R^2$	0.008	0.008	0.032	0.043	–	–	0.063	0.069	0.031	0.031
Within adj. $R^2$	–	–	–	–	–	–	0.053	0.060	0.037	0.038
Pseudo $R^2$	0.002	0.002	0.004	0.006	0.039	0.037	0.04	0.042	0.009	0.009

## Chapter 2

# Managerial Changes and Incentive Evolution in Hedge Funds

### 2.1 Introduction

Hedge funds are “evergreen” investment products with a theoretically infinite lifetime. The investment success of hedge funds is the result of discretionary decisions made by their portfolio managers. The degree of investment flexibility enjoyed by these managers is characteristically high. Thus, a change in portfolio manager can have profound consequences for the hedge fund and its investors. Studying new data on managerial turnover, we find significant dynamics among hedge fund portfolio managers: between 5% and 6% of hedge funds experience manager turnover during our sample period. Fund management teams grow and shrink in size as team members join and leave. Even hedge funds run by a single portfolio manager often see that manager replaced.

We obtain this information by combining historical versions of three hedge fund databases. These databases, widely used in academic research, provide only static information on portfolio managers: for each fund, only the current management is reported. By combining them, individually and across, we can create a manager time series for each fund, and identify turnover events. Next, we match the firms, funds, and managers in our sample with Form ADV filings to add data on each fund’s investor base and managerial incentive structure. Most importantly, we collect the percentage of insider investment (“skin-in-the-game”) in the hedge fund, which we refer to as *SKIN*. We also calculate the percentage of firm equity owned by the individual managers (*STAKE*) and identify whether a manager exercises control over the firm (*CONTROL*). Form ADV filings are historically available, allowing us to determine, for example, the level of *STAKE* a departing manager owned before exiting her fund. We use this novel dataset for five separate analyses, in which we revisit and connect recent hedge fund studies.

**Causes and consequences of managerial turnover** We begin by studying the determinants and consequences of manager-turnover events. Active-manager turnover has been studied in the context of mutual funds. An important difference between actively managed mutual funds and hedge funds is the entrepreneurial nature of hedge fund managers: hedge fund firms are often owned and led by the fund

managers themselves.<sup>1</sup> Most hedge fund firms are indeed small: 53% operate only one fund (Kolokolova, 2011), and 70% of all hedge funds manage less than USD 100 million of capital.<sup>2</sup> In contrast, the mutual fund industry is dominated by fund companies such as Fidelity and BlackRock, which operate hundreds of mutual funds each. Our sample confirms that hedge fund managers tend to be “entrepreneurs” – business partners or sole proprietors – rather than “employees”: 65% of managers own *STAKE* and 62% exercise *CONTROL* at least once during their tenure at a firm. The fund management team (consisting of one or several managers) owns *STAKE* in 82% of observations, and in 80% of observations, at least one person in the team has *CONTROL*.

Our findings, based on 1,365 instances of managerial turnover between 2007 and 2023, align with theories of managerial entrenchment and career concerns. First, managers with *STAKE* or *CONTROL* are significantly less likely to depart, and we find no evidence that departures are preceded by underperformance. Intuitively, the majority of hedge fund managers are entrepreneurs and therefore not the object of hiring-and-firing decisions. This situation contrasts with the mutual fund industry, where involuntary departures after underperformance are common (e.g., Chevalier and Ellison, 1999; Khorana, 1996), as managers are employed at the discretion of a fund management company, which uses manager replacements as an “internal governance” device (Dangl et al., 2006).<sup>3</sup> The hedge fund situation resembles that of small, owner-managed mutual fund families, which have weak internal governance because “the owner is unlikely to sack herself” (Bessler et al., 2018, p. 30).

Second, success in asset raising, as measured by AUM or capital flows, reduces the likelihood of manager departures, which is consistent with the economic incentives of fund operators and managers. Departures are also less likely if fund investors are subject to less liquid redemption terms, indicating that managers value investor inertia. Older funds exhibit lower turnover, which is plausible under the assumption that managerial experience and fund age are related (Boyson, 2003). Experienced managers tend to have higher current incomes, larger personal fund investments, and greater reputational stakes (Boyson, 2010), making both voluntary and involuntary departures less likely. In terms of consequences, we find no evidence that the departure or replacement of its fund manager lowers the subsequent survival probability of a hedge fund.

**Interplay between firm ownership (*STAKE*) and team versus solo management** A second characteristic of hedge funds is the prevalence of solo managers. While mutual funds are predominantly managed by teams (Wang, 2016), 64% of hedge funds in our sample are solo-managed. The hedge fund industry offers a unique laboratory to investigate the quality of decision-making structures as the outcomes in this setting are relevant, observable, and quantified in the form of fund returns. Recent studies documented two stylized facts regarding hedge funds with concentrated versus diversified decision-making structures. First, hedge funds run by firms with dispersed equity ownership perform worse, potentially due to agency frictions and internal conflicts (Gupta & Sachdeva, 2022). Second, team-managed hedge funds underperform solo-managed hedge funds, possibly due to less effective investment decision-making (Y. Chen et al., 2024). These findings may be related, as we find team-managed hedge funds to exhibit

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<sup>1</sup>Anecdotal evidence suggests that it is not uncommon for hedge funds to be started by successful financial-sector employees, whose seed capital is a combination of their accumulated bonuses and outside capital (Axelson & Bond, 2015).

<sup>2</sup>According to HFR, as of the end of Q2 2022.

<sup>3</sup>Voluntary departures of mutual fund managers are less common. Examples include successful mutual fund managers moving to larger mutual funds within or outside their current organization (Hu et al., 2000) or – if they cannot be retained (Deuskar et al., 2011) – to hedge funds (Kostovetsky, 2017).

higher ownership dispersion. Equity ownership can have divergent effects depending on whether the fund is managed by a solo manager or a team of portfolio managers. For solo managers, equity ownership may align incentives and streamline decision-making. In contrast, in a team setting, equity ownership may exacerbate coordination problems and conflicts, such as those related to resource allocation, decision-making authority, and credit for successes or failures (free-rider problem) (e.g., Hoegl et al., 2004).

Relating the two findings, we find that the underperformance of team-managed hedge funds indeed disappears once we introduce *STAKE* as a covariate, weakly suggesting that the underperformance is driven by conflicts arising from equity ownership. While *STAKE* is beneficial for solo managers, for teams, depending on the sample and performance measure, the effect is less positive or even negative. Analyzing hedge funds that transition between solo and team management, we continue to find no evidence that team management leads to underperformance.

**Insider investment (*SKIN*), fund domicile, and the flow-performance relationship** *SKIN* influences fund performance and risk through two main channels: incentives and capital stability. First, *SKIN* helps align the interests of investors and fund managers. By having the manager share in the losses of the fund, it reduces the convexity of the manager’s call-option-like incentive structure (Ma & Tang, 2019).<sup>4</sup> Second, insider capital may benefit capital stability by being more resilient to underperformance than “outsider” (investor) capital, allowing fund managers to pursue riskier strategies (Gupta & Sachdeva, 2022) and avoid uninformed, liquidity-motivated trading (Edelen, 1999). This capital-stability channel offers an explanation for the curious observation that *SKIN* reduces risk-taking by mutual fund managers (Ma & Tang, 2019) but increases risk-taking by hedge fund managers (Gupta & Sachdeva, 2022). The channel is more relevant for hedge funds than for mutual funds, because *SKIN* constitutes a larger percentage of their fund AUM. In our sample, insiders own an average of 21.0% of a hedge fund’s AUM, compared to just 0.04% (Khorana et al., 2007) or, more recently, 0.3% (Ma & Tang, 2019) for mutual funds. While incentivization depends on the dollar amount of *SKIN*, capital stability depends on *SKIN* as a percentage of fund AUM.<sup>5</sup>

Capital stability through *SKIN* allows fund managers to increase risk by, for example, investing in less liquid securities or holding less cash. Insiders can serve as “holders of last resort” for positions that would be most detrimental to liquidate. As a second-order effect of lower potential liquidation costs, investors may perceive the risks stemming from coordinated redemptions by other investors as less severe, which, in turn, lowers the fund’s optimal level of cash holdings (Liu & Mello, 2011). However, since it may not be in the insiders’ interest to be the sole owners of a portfolio of illiquid assets, they might instead exacerbate capital fragility by exploiting their access to superior information and front-running their clients when redemptions loom. Therefore, the effect of *SKIN* on capital fragility is unclear; it depends on both insiders’ behavior and investors’ expectations.

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<sup>4</sup>*SKIN* might also create perverse incentives for fund managers to allocate their most promising, yet least scalable, strategies to the fund vehicles with the highest levels of insider investment (Gupta & Sachdeva, 2022). Table VII in Gupta and Sachdeva (2022) provides evidence supporting the hypothesis that insiders actively restrict outside capital entry into well-performing funds. It is worth noting that additional tests could clarify the causal direction of the relationship between fund “openness” and performance, as the variable indicating a fund’s openness is not time-dependent. Funds classified as “closed” may have previously outperformed and received inflows, leading managers to close them to new subscriptions (Liang & Schwarz, 2011).

<sup>5</sup>A second argument is that mutual funds may lack the investment flexibility to fully exploit capital stability. For example, mutual funds are subject to stringent liquidity regulations, such as the limitation that no more than 15% of a fund’s assets may be invested in illiquid securities, as mandated by SEC Rule 22e-4.

In support of the hypothesis that *SKIN* benefits capital stability, Gupta and Sachdeva (2022) find that funds with higher *SKIN* exhibit a weaker flow-performance relationship. However, their findings may be linked to those of Aragon et al. (2014), who observe a weaker flow-performance relationship for US-domiciled (“onshore”) hedge funds compared to offshore hedge funds. The two studies are related because hedge fund managers and other insiders at hedge fund firms are disproportionately often US citizens who, for tax purposes, prefer to invest in US feeders. Thus, we test whether the weaker flow-performance relationship of high-*SKIN* funds is an artifact of their domicile (or vice versa) by estimating separate regressions for onshore and offshore hedge funds. We show that the findings of both Gupta and Sachdeva (2022) and Aragon et al. (2014) are robust. In an additional analysis, we focus on hedge funds that allow investors to redeem capital on a quarterly basis. While these quarterly redemption dates could theoretically occur at any month-end, we provide evidence that, in practice, calendar quarter-ends are predominantly chosen (March-, June-, September-, and December-end). Even though only net flows can be observed, this phenomenon allows us to roughly differentiate between inflows and outflows. Consistent with the underlying mechanisms proposed by Aragon et al. (2014) and Gupta and Sachdeva (2022), we find that both high-*SKIN* and onshore hedge funds exhibit more muted in- and outflows.

***SKIN* during the hedge fund life cycle** Given the relevance of *SKIN* for the flow-performance relationship, a key question is how *SKIN* evolves over the life of a fund. Boyson (2003) expected that *SKIN* would be high (in percentage terms) during the infancy of a hedge fund, and that managers would increase their personal stakes over time.<sup>6</sup> This is precisely what we find. We observe a U-shaped relationship between *SKIN* and fund age. After an initially high level, *SKIN* first declines, by  $-1.39\%$  per year, as the fund attracts external investors. After an estimated 6.34 years following the fund’s launch, *SKIN* rises again, by  $1.02\%$  per year, as the growth of internal capital outpaces that of external capital. Naturally, changes in *SKIN* are negatively related to inflows of outsider capital, regardless of whether we measure these flows via AUM data (from commercial databases) or via changes in the number of outside investors (from Form ADV). Furthermore, *SKIN* changes and fund fees are positively related, supporting the notion that higher fees increase insider wealth and widen the gap between returns on insider versus outsider capital.

**Leverage and asset returns** Hedge funds can employ significant leverage. We estimate a fund’s gross leverage by dividing its Gross Asset Value (GAV) by its AUM. We make a simple point: the relationship between gross leverage and asset returns – that is, the returns on the assets held in the fund portfolio – depends on the composition of gross leverage, among other factors. We caution against a recently proposed method that infers asset returns by dividing fund returns by gross leverage.

The remainder of this chapter is organized as follows. Sections 2.2 and 2.3 explain our data-collection process and describe our data samples. Empirical results are presented in Sections 2.4 to 2.8: Section 2.4 discusses causes and consequences of managerial turnover. Section 2.5 studies the effects of team management and equity ownership (*STAKE*) on fund performance. Sections 2.6 and 2.7 focus on the effect of insider investment (*SKIN*) on the flow-performance relationship, and on the evolution of *SKIN* during the life of a hedge fund, respectively. Section 2.8 discusses the relationships between gross leverage and asset returns in the context of Barth et al. (2020). Section 2.9 concludes.

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<sup>6</sup> “[A] hedge fund undergoes an incubation period where the only significant investor is the fund manager” (Boyson, 2003, p. 7) and “experienced managers with larger funds probably have significant personal assets at stake” (Boyson, 2003, p. 3).

## 2.2 Data

### 2.2.1 Sample overview

This chapter uses two samples:

- **Sample #1: Main sample**
  - Data period: May 2005 to December 2023
  - Sample period
    - \* Excluding Form ADV data: April 2007 to December 2023
    - \* Including Form ADV data: December 2011 to December 2023
  - Sources: Past versions of TASS, EurekaHedge, and HedgeFund.net; UNION; Form ADV filings
- **Sample #2: EurekaHedge sample**
  - Data period: October 2004 to December 2023
  - Sample period
    - \* Excluding Form ADV data: October 2004 to December 2023
    - \* Including Form ADV data: December 2011 to December 2023
  - Sources: A recent version of EurekaHedge; Form ADV filings

Sample #1 uses historical versions (“snapshots”) of commercial hedge fund databases to track changes in management teams over time. The sample period spans the entire duration for which these snapshots are available, from April 2007 to December 2023. The data period begins in May 2005 to allow us to start estimating variables before the sample period. Sample #2 is intended to be easily reproducible. It uses only a recent version of EurekaHedge and avoids researcher discretion in data preprocessing. The sample period starts in October 2004, because prior returns are backfilled. We use Sample #1 in Sections 2.4, 2.5, and 2.7, where data on historical management teams are required, and Sample #2 in Section 2.5 (for a robustness test) and in the remaining Sections 2.6 and 2.8.<sup>7</sup>

### 2.2.2 Preparation of Form ADV data

We use historical SEC Form ADV filings to obtain data on fund insider investments (*SKIN*), managerial firm equity ownership (*STAKE*), and managerial firm control (*CONTROL*).<sup>8</sup> The Dodd-Frank Act requires

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<sup>7</sup>We include Form ADV data only from December 2011 for three reasons. First, the data on insider investments (*SKIN*) became available in December 2011, as part of additional disclosure requirements imposed by the SEC under the Dodd-Frank Act. Second, the Dodd-Frank Act improved the quality of the Form ADV data. From 1996 to 2011, filing a Form ADV was required from all institutional investment management firms with at least USD 25 million in AUM or at least 15 US clients (Dimmock et al., 2015). However, hedge funds during this period could often evade disclosure even when they operated above those thresholds (Gupta & Sachdeva, 2022). The Dodd-Frank Act aimed to enhance the quality of the data reported by investment advisers. We see evidence of this improvement in the median interval between filings, which shortened from 165 days before December 2011 to 121 days afterward. Third, pre-2011 filings lack unique fund identifiers (“Fund IDs”), which we rely on for sample construction. When matching the firms, funds, and individual PMs in the sample with those in the Form ADV filings, we require matches at both the firm and fund levels. Matching solely on firm or fund names often leads to false identification, because hedge fund names are generic (see, for example, the patterns described in Joenväärä and Tiu, 2023, or <https://www.hedgefundnamegenerator.com/>). We do not use PM names to match firms or funds. Doing so could introduce bias, as the probability of a match would increase with the number of stakeholding PMs.

<sup>8</sup>The historical ADV filings are retrieved from <https://www.sec.gov/foia/docs/form-adv-archive-data.htm>.

all US hedge fund advisers with more than USD 150 million AUM to register with the SEC and to file a Form ADV each year (Jiang, 2024; Mullally, 2022). We observe that filings are updated more frequently than annually, with a median delay of 121 days between filings. To match the monthly frequency of the remaining data, we linearly interpolate the Form ADV data for months without filings. We do not extrapolate the Form ADV data into the past or future.

For *SKIN*, we refer to Section 7.B.(1), Question 14 of Form ADV Schedule D: “What is the approximate percentage of the private fund beneficially owned by you and your related persons?” The *SKIN* data have two limitations: they are provided at the fund level rather than the personal level; and the definition of “related persons” is not limited to portfolio managers but includes all individuals with potential influence or conflicts of interest (see Appendix 2.A.1 for a definition of “related persons”). Master-feeder structures pose a challenge in determining *SKIN*. In such structures, one or several feeder funds invest essentially all of their assets into a master fund, which then executes the actual investment strategy (Aragon et al., 2014). Investors typically choose between several feeders, each with different tax and regulatory implications (Cumming et al., 2015). Although Form ADV generally requires separate reporting for each entity (feeder and master funds), in practice, the data reported at the master-fund level often reflects aggregated information from the feeder funds. To illustrate, Figure 2.1 compares the number of investors reported at the master-fund level with the sum of investors across the respective feeder funds for all 2,089 master hedge funds in the Form ADV dataset. The association is strong but imperfect. If the numbers are aggregated, then the number of investors reported for the master fund should not be lower than the total number of investors in the feeder funds. However, we find that this is not the case for 36% of the observations.<sup>9</sup> Similarly, in 21% of cases where *SKIN* is present in the feeder funds, no *SKIN* is reported at the master-fund level. To reconcile the different reporting approaches, we apply the following rule: if the number of investors in the master fund is lower than the sum of investors in the respective feeder funds, we assume that the reporting firm chose not to report aggregated values at the master-fund level. For these funds, we estimate *SKIN* as the sum of all *SKIN* values across all fund vehicles (feeder and master), weighted by gross asset value (GAV). This assumes that the fund employs the same degree of leverage across all vehicles in the master-feeder structure.

For *STAKE* and *CONTROL*, we rely on Schedules A and B of Form ADV. Schedule A reports direct ownership, while Schedule B reports indirect ownership. We calculate the total ownership of each manager by aggregating her direct and indirect stakes. For example, a manager may own 50% of a hedge fund firm through a combination of a 25% direct stake (disclosed in Schedule A) and a 50% stake in a holding company (Schedule B), which in turn owns 50% of the firm (Schedule A). Schedule A does not provide exact ownership percentages but instead distinguishes between six ranges: “NA: Less than 5%”, “A: 5% but less than 10%”, “B: 10% but less than 25%”, “C: 25% but less than 50%”, “D: 50% but less than 75%”, and “E: 75% or more”. For direct stakes, we use the algorithm described in Dimmock et al. (2015, Appendix A) to infer the maximum amount of information from these codes. This algorithm cannot be applied to indirect stakes, because Schedule B only reports stakes of 25% and above (codes C to E). Therefore, we use simple midpoints (“C”: 37.5%; “D”: 67.5%; “E”: 87.5%) for Schedule B, and we scale

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<sup>9</sup>In 31% of cases, the number of investors reported for the master fund is identical to the total number of investors across the feeder funds. This indicates that the master-fund figure is indeed often an aggregation of the feeder funds’ numbers, and that the relationship observed in the figure is not merely due to a potential correlation between these numbers. Additionally, in many cases, the number of investors at the master-fund level is slightly higher than the feeder aggregate. This supports, rather than contradicts, the aggregation story, because direct investments into master funds, bypassing the feeder structure, are often possible, but rare.

down individual stakes in an entity if the total ownership of the entity would exceed 100%.

We remove 7.3% (Sample #1) and 5.1% (Sample #2) of Schedule-A filings, because they are implausible. Specifically, the maximum potential ownership must total at least 100%, and the minimum must not exceed 100%. For example, filings with ownership codes such as “BCCCC” (minimum 110%) or “ABBB” (maximum 85%) are filtered out. Even after excluding these filings, the stake aggregation may still fail, typically due to minor spelling differences or omissions (such as “Ltd” instead of “Ltd.”) within a filing.<sup>10</sup> In these cases, we manually correct the errors using previous or subsequent filings by the same filer. Given the tedious nature of these corrections, they are performed only for firms in Sample #1 associated with funds that experience a manager-turnover event. For all other firms, the erroneous filings are removed, resulting in the loss of an additional 2.8% (Sample #1) and 2.7% (Sample #2) of filings.

*CONTROL* is a binary variable taken from Schedule A. The variable indicates whether the individual exercises “Control”, defined as the power to direct the management or policies of the firm, whether through ownership of securities, by contract, or otherwise (see Appendix 2.A.1 for the definition). Notably, an individual without *STAKE* may still exercise *CONTROL*. For managers not listed in Schedule A or B, even though we can identify their firms in Form ADV, we follow Dimmock et al. (2015) in assigning them 0% *STAKE* and no *CONTROL*.

### 2.2.3 Construction of Sample #1

We obtain historical information on hedge fund managers by utilizing past versions (“snapshots”) of three hedge fund databases: EurekaHedge, HedgeFund.net, and TASS. Table 2.1 summarizes the availability of these snapshots. For example, we have at least one TASS snapshot for 180 out of the 202 months between April 2007 and December 2023. The largely monthly frequency of our snapshots matches the frequency of fund return and fund AUM observations. We assume that manager changes become effective at the month-end prior to them being reported to the databases. As for the Form ADV data, we interpolate firm, fund, and manager names data for months without snapshots, but do not extrapolate.

The three databases each assign permanent identifiers to the individual funds. We use these identifiers to track the funds throughout the snapshots and to match our sample with the UNION dataset.<sup>11</sup> The UNION dataset merges five major commercial databases: BarclayHedge, EurekaHedge, Hedge Fund Research (HFR), Morningstar, and TASS. Matching our sample with UNION provides additional data on the hedge funds and helps us identify duplicate funds and firms within and across the three databases. UNION regards two funds as duplicates if their returns are highly correlated (0.99 or more) and their average returns and AUM are similar (within 10% of each other). Since HedgeFund.net is not a part of the UNION database, we exclude HedgeFund.net funds that do not experience a manager turnover event. We manually search for the remaining, event-experiencing funds within UNION based on return correlations and name comparisons. Thanks to the overlap among the databases, 90% of event-experiencing HedgeFund.net funds are included in UNION. We manually merge the historical HedgeFund.Net performance files, because the database does not include closed (“dead”) funds.

When a fund first enters a database it can “backfill” its historical returns, which may be biased due

<sup>10</sup>Form ADV provides “OwnerIDs”, but they are rarely useful; the most frequent values are “FOREIGN”, “FOREIGN ENTITY”, “xxx-xx-xxxx”, “00-0000000”, “N/A”, and “NONE”.

<sup>11</sup>As mentioned in Chapter 1, Agarwal et al. (2017) provide details on a previous version of the UNION dataset. The dataset has since been updated to include data through December 2022, and the BarclayHedge database has been added.

to incubation and selection biases (Fung & Hsieh, 2000). To address this “instant history” bias, we use the database addition dates provided by TASS and EurekaHedge to exclude returns before a fund’s database inclusion date, as proposed by Fung and Hsieh (2009), Malkiel and Saha (2005) and Posthuma and van der Sluis (2003). For the 4% of funds lacking addition dates, we infer these dates from the fund’s first appearance in our historical snapshots (as in Jorion and Schwarz, 2019). For the remaining 0.3% of funds with missing addition dates and database entry on or before the start of the historical snapshots, we exclude observations from fund launch until the earlier of 12 months after launch or the fund’s first appearance in the snapshots (as in Bali and Weigert, 2024).

We exclude funds that are not part of the UNION dataset. We also exclude (1) fund-of-funds, (2) funds denominated in a currency other than USD, and (3) funds that report gross (instead of net) returns at quarterly (instead of monthly) frequency. Ultimately, Sample #1 consists of data for 5,274 USD-denominated hedge funds, 2,094 of which are matched to Form ADV filings.

## 2.2.4 Construction of Sample #2

Sample #2 is drawn from the EurekaHedge database and consists of 12,692 USD-denominated hedge funds, of which 534 are algorithmically mapped to Form ADV filings. As for Sample #1, we require that both the firm and fund names match between EurekaHedge and Form ADV. We then manually link the managers between the two data sources.<sup>12</sup>

## 2.2.5 Variable construction

**AUM flows** We approximate fund flows as the change in AUM, adjusted for fund return (Sirri & Tufano, 1998). For the 12-month interval, we use the following formula (analogously for other intervals):

$$FLOW12_{i,t} = \frac{AUM_{i,t}}{AUM_{i,t-12}} - \prod_{j=0}^{11} (1 + RET_{i,t-j}), \quad (2.1)$$

where  $AUM_{i,t}$  represents the assets under management (AUM) of fund  $i$  at the end of month  $t$ , and  $RET_{i,t}$  is the return of fund  $i$  during month  $t$ . Flows are thus expressed as a fraction of AUM. AUM data, as provided by the databases, are frequently stagnant, missing, or otherwise unreliable. If missing, we extrapolate AUM data for up to two months. We do not extrapolate AUM data points if they are stagnant (i.e., unchanged for three consecutive months despite positive or negative fund performance). We require at least USD 5 million in AUM to calculate flows, and we winsorize the flow data at the 1st and 99th percentiles. For non-missing AUM observations, we impose a lower threshold of USD 1 million to avoid extreme log-transformed values.

**Returns and risk-adjusted performance** Fund returns are obtained net-of-fees from the databases. We consider three measures of risk-adjusted performance. First, we use “style-adjusted returns” as our main measure of manager skill.<sup>13</sup> Style-adjusted returns are calculated as the deviation of a fund’s return

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<sup>12</sup>We choose EurekaHedge because it includes data on fund leverage limits, which we use in Section 2.8. The database also provides two well-populated data fields to mitigate backfill bias and exclude duplicate share classes (“Date Added” and “Unique”), respectively, facilitating replication. *R* scripts are available from the authors.

<sup>13</sup>Style-adjusted returns have the advantage not to require the estimation of factor loadings, which avoids a potential multi-period sampling bias (Fung & Hsieh, 2000). The 7- or 8-factor models of Fung and Hsieh (2004), while standard in the literature, were designed for diversified portfolios of hedge funds. Applied to individual hedge funds that do not engage in the strategies reflected in the models, the models may be inadequate and prone to overfitting.

from the average return of funds following the same investment style (e.g., Yin, 2016):

$$SA_{i,t} = RET_{i,t} - \frac{1}{N_s} \sum_{k=1}^{N_s} RET_{k,t}, \quad (2.2)$$

where  $SA_{i,t}$  is the style-adjusted return of fund  $i$  in month  $t$ , and  $N_s$  is the number of funds that follow the same style  $s$  as fund  $i$ . We distinguish eight hedge fund styles, as in the UNION dataset: “Credit”, “Equity”, “Event Driven”, “Macro”, “Managed Futures / CTA”, “Multi-Strategy”, “Relative Value”, and “Other or not specified”. Average style-adjusted returns over the prior 12 months are denoted as  $SA12$ .

Second, we use CAPM alpha (Lintner, 1965; Sharpe, 1964) to examine determinants of fund flows. While investors, who infer managerial skill by observing fund performance (Berk & Green, 2004), generally respond positively to past performance as measured in various ways, Agarwal et al. (2018) find that hedge fund flows are better explained by CAPM alpha than by raw fund returns or by alphas from more sophisticated models. Following Agarwal et al. (2018), we estimate the factor loadings using monthly data over 24-month rolling intervals:

$$RET_{i,t} - RF_t = a_i + \beta_i RMRF_t + \varepsilon_{i,t}, \quad (2.3)$$

where  $RET_{i,t} - RF_t$  is fund  $i$ 's after-fee excess return over the risk-free rate in month  $t$ .  $RMRF$  is the excess return on the market, calculated as the value-weighted return of selected US-listed and US-incorporated firms, minus the one-month T-bill rate.<sup>14</sup> Further following Agarwal et al. (2018), we calculate CAPM alpha ( $\alpha_{i,t}$ ) as any return in excess of the risk-free rate that is not explained by exposure to the market factor:

$$\alpha_{i,t} = a_i + \varepsilon_{i,t}, \quad (2.4)$$

We then compute the average CAPM alpha over the previous 12 months ( $CA12$ ) or the entire 24 month period ( $CA24$ ) of each interval. Finally, we calculate the relative rank in terms of  $CA12$  and  $CA24$  for each fund and month. For  $CA12$ :

$$RANK\_CA12_{i,t} = \frac{\text{rank}(CA12_{i,t})}{N_t + 1}, \quad (2.5)$$

where  $N$  denotes the number of funds in month  $t$  with non-missing  $CA12$ . This ranking provides a standardized measure of relative performance across funds.

Third, following the hedge fund literature, we incorporate also alpha from the Fung and Hsieh (2004) seven-factor model:

$$RET_{i,t} - RF_t = a_i + \beta_{1,i} SPXRF_t + \beta_{2,i} SCMLC_t + \beta_{3,i} BD10RET_t + \beta_{4,i} BAAMTSY_t + \beta_{5,i} PTF SBD_t + \beta_{6,i} PTF SFX_t + \beta_{7,i} PTF SCOM_t + \varepsilon_{i,t}, \quad (2.6)$$

where  $SPXRF$  is the excess return on the equity market, proxied by the total return on the S&P 500 index minus the risk-free rate;<sup>15</sup>  $SCMLC$  is the return on a size-spread factor, calculated as the difference between the total returns on the Russell 2000 index and the S&P 500 index;  $BD10RET$  and  $BAAMTSY$

<sup>14</sup>Returns on the factors  $RF$  and  $RMRF$  are sourced from Kenneth French's data library: [https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data.Library/f-f\\_factors.html](https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data.Library/f-f_factors.html).

<sup>15</sup>Prior literature differs in whether to deduct the risk-free rate from the S&P 500 index return (e.g., Fung et al., 2008) or not (e.g., Gupta and Sachdeva, 2022). We choose to do so because the return on the S&P 500 should incorporate the risk-free rate.

are the returns on two bond-oriented risk factors – the change in the 10-year Treasury constant maturity yield and the change in Moody’s Baa yield less the 10-year treasury constant maturity yield; and *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the returns on portfolios of lookback straddles on bonds, currencies, and commodities, respectively, designed to model the returns of trend-following strategies (Fung & Hsieh, 2001).<sup>16</sup> Average alphas over 12-month periods (*FH12*) and the corresponding ranks (*RANK\_FH12*) are calculated in the same manner as for CAPM alpha.

## 2.3 Descriptive statistics

Table 2.2 summarizes Sample #1, which consists of 5,274 hedge funds during May 2005 and December 2023. 64% of funds in Sample #1 are managed by a single portfolio manager, which is similar to the 60% observed by Y. Chen et al. (2024) using different data. The average fund generates an after-fee return of 0.31% per month, manages USD 291 million of capital, and has 9.3 years of return history. Median management and performance fees are 1.5% and 20% per annum, respectively. The bottom part of Table 2.2 considers only the 2,094 of hedge funds that have been matched to Form ADV filings. The PMs on average own a 30.7% *STAKE* and exercise *CONTROL* in 66.5% of observations. Thus, in the majority of observations, the fund managers have the power to direct the management or policies of their firms, evidencing the prevalence of “entrepreneurs” in the hedge fund industry. For brevity, we omit summary statistics for Sample #2.

Table 2.3 reports the average *STAKE* and the prevalence of *CONTROL* by PM gender and age group. Female PMs on average own less *STAKE* than male PMs, and *STAKE* increases with manager age. The same patterns appear for *CONTROL*. However, since female PMs, more often than male PMs, are marketers who have been misclassified as PMs (see Section 3.2.2), differences between male and female PMs may reflect differences between PMs and marketers. Figure 2.2 shows histograms of *SKIN* and *TSTAKE*, which is the cumulative *STAKE* of the management team. Both *SKIN* and *TSTAKE* display a “dumbbell” distribution.<sup>17</sup> Strikingly, in 49% of observations, the management team owns at least half of the firm equity.<sup>18</sup>

## 2.4 Causes and consequences of managerial turnover

### 2.4.1 Event identification

We identify manager-turnover events by detecting changes in the “portfolio manager” data field between two consecutive database snapshots from any provider. We manually adjust the manager names to remove spurious changes, such as spelling variations (e.g., “Rob” instead of “Robert”), name changes due to marriage, or the addition of titles (e.g., “Ms.,” “Mr.”) or designations (e.g., “PhD”, “CFA”). Since our focus is on natural persons, we exclude any entities listed as portfolio managers (e.g., “XYZ Capital Investment Committee”).

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<sup>16</sup>Factor definitions along with the returns on the model’s trend-following factors are taken from David A. Hsieh’s data library: <https://people.duke.edu/~dah7/HFRFData.htm>.

<sup>17</sup>For *SKIN*, this was observed also by Gupta and Sachdeva (2022).

<sup>18</sup>The results are materially unchanged if we first compute the average of each team’s ownerships across time, and then compare these averages with each other.

We apply several filters, which narrow the dataset from 2,954 to 1,365 events. The most significant reduction is the removal of 621 duplicate events, which occur when a fund is represented in multiple databases or has multiple share classes within a single database. Additionally, (1) we clean our data to ensure changes are identified with at least semi-annual accuracy, excluding 295 events. Specifically, for EurekaHedge and TASS, we exclude changes if the recorded data points are more than six months apart. This exclusion is not needed for HedgeFund.net, which records the date when fund information is updated. (2) We remove inconclusive data points, which occur when a single database lists different managers for the same fund at the same time. These discrepancies arise when a database assigns different managers to funds identified by UNION as duplicates. (3) Similarly, we remove nonconsecutive events where, within a database, the replaced management team differs from the previously replacing team. (4) We exclude manager changes that are later reversed, as these are likely due to data entry errors rather than actual turnover events. They might also result from temporary departures, such as sabbaticals, which are not our focus. (5) If an event is recorded in multiple databases at different times, we retain only the data from the database that records the event first. (6) If several databases observe the same replacing managers but different outgoing managers, we give preference to the earlier event. (7) We remove events that occur outside of the fund’s return series, that is, before the first return observation or after the last. After applying these filters, we observe a total of 1,365 portfolio manager changes across 1,100 funds.

Panel A of Table 2.4 reports the number of events by their effect on team size. When a manager change occurs, the size of the team may increase, decrease, or remain the same. Simultaneously, all, some, or none of the team members may be replaced. Management teams are generally small: 70% of hedge funds are managed by no more than two individuals, both before and after the event. The most common event is the replacement of a single manager (356 instances). Decreases in team size (542 instances) are more frequent than increases (324 instances). Panel B provides a breakdown of the number of manager departures and arrivals by fund AUM, style, database provider, manager *CONTROL*, and manager *STAKE*. Most events stem from EurekaHedge.<sup>19</sup> Although the majority of managers have *CONTROL*, fewer than a third of the events involve managers with *CONTROL*. We explore factors determining manager turnover in Section 2.4.2.

**Data quality** Previous studies primarily used information about current team members to study past fund variables. Exceptions include Ellul et al. (2020) and Lu et al. (2022, 2024). The former examine career trajectories of hedge fund managers, while the latter explore the impact of managers from minority groups on fund performance. Our study differs in that we do not rely on public sources (such as *LinkedIn*) to determine employment start and end dates, and thereby avoid a potential self-selection sampling bias and significant data loss. Instead, the high (mostly monthly) frequency of the database snapshots allows us to infer employment dates directly from the creation dates of the snapshots. This approach also captures changes in responsibilities that may not be reflected in job titles. For instance, a retiring founder might voluntarily relinquish her portfolio-management responsibilities without changing her title on *LinkedIn*. Furthermore, it is common on *LinkedIn* to mention only the last (and typically highest) position held at an employer. If employees begin in junior roles, such as “Research Analyst”, before gaining portfolio-management responsibilities, then the *LinkedIn* employment start dates are misleading.

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<sup>19</sup>This is likely caused by the fact that manager names are much better populated in EurekaHedge than in TASS, where we have to remove 55% (!) of funds, because no manager name is reported. After this removal, the providers do not differ in the prevalence of events, with approximately 5% (EurekaHedge), 5% (HedgeFund.Net), and 6% (TASS) of funds experiencing events.

Historical hedge fund database versions have been widely used in the academic literature on hedge funds – to study changes in fund fees (Deuskar et al., 2013; Schwarz, 2007), redemption terms (Hong, 2014), and leverage (Liang & Qiu, 2019), and to explore decisions to open or close funds for investment (Liang & Schwarz, 2011).<sup>20</sup> A challenge for these studies – and ours – is that funds may report such changes only with a delay. Moreover, changes in database entries might not reflect real-world events but could also result from the correction of input errors.

Do database changes accurately reflect real-world events? The Form ADV data allows for a test of data quality. Specifically, we focus on the subset of PMs, who (1) are involved in a turnover event and (2) appear in the Form ADV Schedule A/B data. Following the approach used for the database snapshots, we infer the “arrival” and “departure” of PMs by comparing adjacent Schedule A/B filings of individual fund firms, assuming that firm control and general firm affiliation are related. This relationship must be imperfect given that firm control and employment may differ; for example, a PM may acquire a stake prior to being hired or retain a stake after departing.<sup>21</sup> In total, there are 502 events (284 departures and 218 hires) of PMs who we can identify in Form ADV filings of their respective firms. 27% of these events (78 departures and 57 hires) also happen within the Form ADV filings.<sup>22</sup>

The upper charts of Figure 2.3 compare the event dates inferred from snapshots with those inferred from Form ADV filings. The association is stronger for departures (left-hand chart) than for hires (right-hand chart). 68% of departures and 60% of hires are reflected in the Form ADV filings sooner than in the database snapshots. On the median, a “departure” (“hire”) happens in the Form ADV data 134 days (275 days) sooner than in the database snapshots. A natural explanation is that firms take mandatory regulatory filings more seriously than voluntary updates to commercial databases. The bottom charts of Figure 2.3 exploit the “Date Title or Status Acquired MM/YYYY” data field in Form ADV Schedule A. This field specifies when a person listed on Schedule A obtained their current role in the firm. For example, if the person became the firm’s Chief Financial Officer in March 2020, the field would read “03/2020”. For each combination of person and firm, we consider the earliest of these role-acquisition dates. The chart on the bottom left reveals that managers usually acquire their first position within a firm already before appearing as a fund manager in the databases. Either fund managers are relatively often hired internally, or the database information is inaccurate. The bottom-right chart suggests that individuals are timely included in Form ADV filings.

To summarize, database changes seem to provide only imprecise information about real-world events. The inaccuracy is problematic for studies that depend on precise information about the timing of such events, such as studies conducting difference-in-differences analyses. Event dates for departures seem to be more accurate than event dates for hires. We conduct our analyses with consideration of these limitations.

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<sup>20</sup>Hedge fund database snapshots have also been used to investigate hedge funds that revise returns previously reported to databases (Patton et al., 2015), to measure the delay with which funds report returns to databases (Aragon & Nanda, 2017), and to identify database addition dates (Jorion & Schwarz, 2019). However, these studies address research questions for which a potential reporting delay would be inconsequential. Similarly, Liang et al. (2019) use historical TASS versions to improve the accuracy of their dataset.

<sup>21</sup>An alternative test could compare fee changes inferred from TASS snapshots with changes in the TASS fee-history file, which is used in Agarwal and Ray (2012), Deuskar et al. (2013) and Liang (2001).

<sup>22</sup>That is, a PM who is “hired” according to comparisons of adjacent database snapshots also appears in the respective firm’s Form ADV filings only after the firm’s initial filing, and a “departing” PM disappears from the filings at some point.

## 2.4.2 Causes

When do fund managers join and leave hedge funds? To investigate the determinants of managerial turnover, we estimate multinomial logistic regressions. The analysis is twofold: at the manager level, it explores the patterns of departures and hires among individual portfolio managers. At the fund level, we categorize manager turnover events into three types: hires (without simultaneous departures), departures (without simultaneous hires), and replacements (simultaneous hires and departures). In each regression, we also include the event of fund closure (“fund death”) as a reference point, since the determinants of fund closure are well understood (e.g., Liang, 2000; Liang and Park, 2010). All variables are observed at annual frequencies to avoid autocorrelation in the explanatory variables.<sup>23</sup> To obtain more reliable estimators and facilitate interpretation, non-dummy variables are standardized to unit variance.

**Manager-level regressions** The results of the regressions on manager level are presented in Panel A of Table 2.5. The regression on the right-hand side excludes variables obtained from Form ADV filings, allowing it to cover a longer time period (April 2007 to December 2023) than the regression on the left-hand side (December 2011 to December 2023).

*Ownership and control:* *STAKE* and *CONTROL* have strong negative effects on the likelihood of a manager arrival or departure. The odds of a manager departure decrease by 69.6% ( $= 1 - \exp(-1.191)$ ) if the manager exercises *CONTROL*.<sup>24</sup> Intuitively, a manager with *STAKE* or *CONTROL* is both more willing and more able to continue managing the fund. In terms of willingness, managers with *STAKE* may face higher switching costs as their financial interests, and potentially their professional reputation, are more closely tied to the fund’s success. In terms of ability, managers with *STAKE* or *CONTROL* occupy a privileged position within the organizational structure of the operating firm, which shields them from the risk of termination.

*Performance and risk:* The results support the view that hedge fund managers are entrepreneurs who depart voluntarily rather than being forced out. Specifically, we find no evidence that a PM’s departure is triggered by fund underperformance. Instead, after controlling for *STAKE* and *CONTROL*, our analysis suggests that past positive style-adjusted performance (*SA12*) increases the likelihood of departure.<sup>25</sup> This pattern contrasts sharply with mutual fund managers, whose departures are more often the result of termination after underperformance. We discuss two implications.

First, the results support a stronger flow-performance relationship in hedge funds than in mutual funds. When hedge fund managers are immune to being fired, investors cannot rely on involuntary departures as a mechanism to sanction underperformance. In the absence of effective internal governance, the responsibility for performance evaluation falls more heavily on the investors. Recognizing this responsibility, investors

<sup>23</sup>We obtain qualitatively identical results with monthly instead of annual observation frequency.

<sup>24</sup>In an unreported robustness test, we exclude observations where *STAKE* and *CONTROL* have been set to zero because the PM is not listed in the firm’s Form ADV filings. Although it is reasonable to assume that managers not listed in Schedule A/B lack *STAKE* and *CONTROL* (Dimmock et al., 2015), these cases could introduce bias, as events might appear in Form ADV earlier than in the database snapshots (see Section 2.4.1). For example, in our dataset, a PM with *CONTROL* must be listed in Schedule A/B, whereas a PM without *CONTROL* might not be. If a PM departs and this departure is reflected first in the Form ADV filings, the database snapshot might no longer show the PM as having *CONTROL* when the departure is recorded. This could falsely suggest a link between the absence of *CONTROL* and the likelihood of departure. Still, when we remove these potentially problematic observations – where a PM is assigned no *STAKE* or *CONTROL* because the PM is not listed in Schedule A/B – the results for both hires and departures remain qualitatively unchanged.

<sup>25</sup>In unreported regressions, we confirm that these results hold across various performance measures, namely raw returns, CAPM alpha, and Fung-Hsieh 7-factor alpha.

may compensate by responding more strongly to performance, thereby intensifying the flow-performance sensitivity in hedge funds.

Second, since institutional investors have been found to be surprisingly resilient to underperformance (Goyal et al., 2023), our results offer an explanation for the concentrated nature of the hedge fund industry.<sup>26</sup> While underperforming hedge fund managers may not be at risk of being fired, they also lack outside options: chances of reemployment in the hedge fund industry are generally low (Brown et al., 2001), and having worked for a hedge fund that was liquidated has a scarring effect on the manager's future career (Ellul et al., 2020). The combination of entrepreneurial managers lacking career mobility and investors tolerating underperformance aligns with the general observation of a hedge fund industry that is dominated in terms of number, but not in terms of assets, by small funds.

*Investor flows and AUM:* Higher AUM and more positive net capital flows (*FLOW12*) reduce the likelihood of managerial turnover. Since fee revenues scale with fund AUM, a managerial departure becomes less attractive for both fund operators and managers if the fund succeeds in raising assets. Inflows increase the fund's profitability and, in turn, the willingness of entrepreneurial PMs to stay. For PMs without control, inflows may reflect perceived "marketing ability", which, as demonstrated for mutual fund managers, enhances job security (Kostovetsky & Warner, 2015).

*Team size, manager age, and manager gender:* The coefficient estimates for *TEAMSIZ*E suggest that larger teams are more likely to experience departures, while smaller teams are more likely to experience hires. Notably, this finding is likely not an artifact caused by data entry limits given that almost all events occur within teams that are smaller than the limit (see Table 2.4, Panel A). Male PMs are less often involved in turnover events. However, as will be discussed in Chapter 3, female PMs are disproportionately often marketers who have been misclassified as PMs, and marketers may have higher career mobility than PMs. The negative coefficient for manager age (*MAGE*) in the right-hand regression could result from the positive relationship between manager age and both *STAKE* and *CONTROL* (see Table 2.3).

*Fund age:* The negative coefficient estimates for *FAGE* suggest that older funds experience lower turnover. Assuming, as Boyson (2010) argues, that fund age and manager experience are related, these results align with managerial career concerns. Specifically, experienced managers have more to lose in terms of income, reputation, and personal fund investments (Boyson, 2003). These factors make both voluntary and involuntary departures less likely: income and reputation discourage the manager from departing, while a manager's reputation and personal fund investments increase the costs a fund operator would incur to replace the manager.

*Investor illiquidity:* The negative coefficient estimates for the restriction period ( $\log(\textit{REST})$ ) suggest that managers are more willing or able to stay if investors cannot easily redeem their shares. The variable is calculated as the sum of the redemption frequency (the number of days between two consecutive redemption dates) and the advance notice period required before redemption (Agarwal et al., 2024).

*Number of snapshots, number of fund appearances:* We control for both the number of database snapshots available in each month (*NSNAP*) and the number of times a fund appears in the snapshots within a given month (*NAPPEAR*). A single fund may have multiple appearances due to duplicate share classes or inclusion in multiple databases. The more snapshots available and the more frequent the appearances, the more manager changes we can detect.

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<sup>26</sup>According to HFR, as of the end of Q2 2022, the hedge fund industry is highly concentrated: the 70% of hedge funds with less than USD 100 million in assets under management (AUM) account for only 2% of industry-wide AUM. 11% of funds have AUM above USD 1 billion, yet control 84% of industry assets.

**Fund-level regressions** The results for the fund-level regressions are reported in Panel B of Table 2.5. The findings generally confirm the prior results. We find evidence that insider ownership (*SKIN*) reduces the incentive to add a portfolio manager. However, the number of fund-level events is very limited when including the Form ADV data, so these findings should be interpreted with caution. In summary, the results suggest that managers with *CONTROL* or *STAKE* are less likely to depart, which we attribute to their privileged position within the operating firm’s organizational structure. Given that such entrepreneurial managers are the norm rather than the exception in the hedge fund industry, we find no evidence that hedge fund managers are forced to depart after underperformance – unlike mutual fund managers.

### 2.4.3 Consequences for fund survival

Are funds with managerial turnover more at risk of subsequent closure? To investigate, we classify as closed (or “dead”) all funds that stop reporting to the databases for an undeclared reason or for any reason other than a fund merger or split. These “dead” funds include both failures, which are preceded by outflows and negative performance, and voluntary liquidations (Liang & Park, 2010). While fund failure is the more negative outcome, we argue that investors would be wise to avoid voluntary liquidations as well. Beyond the costs of dissolving the fund structure,<sup>27</sup> fund closures also entail market-impact and other transaction costs during the liquidation of the portfolio. Hedge funds with illiquid portfolios may impose discretionary liquidity restrictions (Aiken et al., 2015a), delaying the payout of redemption proceeds.

We expect manager departures to be a negative signal for fund survival, regardless of whether the departure is voluntary or involuntary. Managers and operators have access to private information and are in a privileged position to evaluate their funds’ investment (fund returns) and business (fee revenues) prospects. Departures may also be a sign of firm-internal issues, such as personal conflicts among the investment-team members as well as operational or compliance issues.

By design, hedge funds that experience a manager event necessarily survive until then. As a result, the survival times of event funds are inflated by survivorship bias. Therefore, the lifetimes (from fund inception to closure) of event funds cannot be directly compared with those of non-event funds. Nor can we compare the post-event survival times of event funds with the since-inception survival times of non-event funds, as fund age positively affects survival (Brown et al., 2001). To avoid survivorship bias and allow for a fair comparison, we apply a propensity-score-matching approach. This method allows us to identify a sample of control funds with similar likelihoods of death as the event funds at the time of manager turnover. We then compare the remaining survival times of event and control funds, disregarding their previous lifespans.

Thus, we first calculate the likelihoods of fund closure (“propensity scores”) using a binary logit regression, with fund survival and closure as the two possible outcomes. We follow Aiken et al. (2015b) and Liang and Park (2010) in their choice of explanatory variables for this model. Specifically, we include fixed effects for investment style and year, as well as two dummy variables indicating whether AUM are stagnant (*STAGNANT*) and whether the fund’s auditor is among the “big four” (*BIG4*). Investment style and market environment may influence how investors assess fund risk and return, thereby impacting

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<sup>27</sup>Fund dissolution costs can include deregistration fees, expenses for an ad-hoc audit, and, in the case of younger funds, additional amortization expenses resulting from the accelerated amortization of unamortized “setup” or “organizational” costs incurred during the establishment of the fund. These costs are generally charged to the fund.

fund survival. Stagnant AUM data may signal a decision not to disclose an AUM reduction, while an auditor outside of the “big four” could indicate operational risk, which poses a threat to survival (Brown et al., 2008). Finally, we add the restriction period (*REST*) to control for share restrictions, as suggested by Liang et al. (2019).

Panel A of Table 2.6 reports the results of this regression analysis. We select the model in Column (5) for estimating the propensity scores because it produces the lowest Bayesian Information Criterion (BIC) while retaining at least as many observations as the other models. The AUC (area under the ROC curve) for this model (5) is 0.714, indicating that if two funds are randomly selected – one that has “died” and one that has not – there is a 71.4% chance that the model will correctly assign a higher probability of “death” to the fund that actually “died” compared to the one that did not. This suggests that the model has a good, though not perfect, ability to distinguish between funds that “die” and those that survive.

Next, we perform 2-to-1 matching without replacement, given the large number of potential peers and the potential to increase the precision of the estimates compared to 1-to-1 matching. We match on the logit of the propensity scores rather than the raw scores, as the logit is more likely to be normally distributed than the propensity score itself (Austin, 2011). Panel B of Table 2.6 assesses the success of the matching process by comparing the means of the selected variables between control funds and event funds. For both events, the only statistically significant difference between the two groups is in fund age (*FAGE*), with funds in each event group being younger on average than those in the control group. There are no significant differences in the other variables.

We then calculate the remaining survival times of all funds. Survival time is right-censored for 50% of event funds and 48% of control funds. Death is not observed for these funds because they either survived until the end of our sample period (December 2023) or dropped out of the database due to fund merger or split. Notably, death is observed for 60% of all funds in the overall sample, highlighting the survivorship bias mentioned earlier.<sup>28</sup>

Figure 2.4 presents Kaplan-Meier plots of funds’ estimated survival probabilities over time. Panels A and B regard arrivals and departures of managers, respectively. Each panel compares two groups of funds: those experiencing managerial turnover (event group) and those that do not (control group). Against our expectations, we find no evidence that a manager’s departure or hire affects the risk of subsequent fund closure. For instance, funds with departing managers have a median survival time of 64 months after the event, which is 10 months shorter than the remaining survival time of the propensity-score matched peers (74 months). However, the differences are overall not statistically significant.

Panel C of Table 2.6 compares the remaining survival times of event and control funds using a Cox Proportional Hazards model, which has been widely used to study hedge fund survival (e.g., Boyson, 2003; Brown et al., 2001; Liang and Park, 2010; Liang and Qiu, 2019). The dependent variable is the survival time in months after the manager event. Like the Kaplan-Meier plots, the Cox model accounts for the right-censoring of the data. Each column in the panel represents a different regression, where an indicator variable (*EVENT*) distinguishes the funds that experience the specific manager event from the propensity-score matched control funds. We again find no evidence that manager departures or hires affect the remaining survival times of hedge funds. Unexpectedly, higher fund returns (*R12*) and higher

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<sup>28</sup>We know the death date for 73% of the funds (see Table 2.2). However, some of these death dates fall outside of the date ranges for which we have snapshots. For example, we may know from the UNION dataset that a fund in the HedgeFund.net database dies in 2013. However, as the HedgeFund.net snapshots end in 2011, we cannot analyze this death, because we do not know whether the manager has remained the same.

AUM ( $\log(AUM)$ ) are found to *reduce* the survival times. These counterintuitive results may be caused by the matching procedure. In unreported analyses, we distinguish between turnover among managers with and without *CONTROL*, again obtaining insignificant results.

Finally, in Panel D, we repeat the exercise of Panels A and B on the fund level. Specifically, we use the earlier-described fund-level events: hires without simultaneous departures (“PM additions”), departures without simultaneous hires (“PM exits”), and replacements (“PM replacements”). In specifications II, IV, and VI, the variable *PERC\_J* (*PERC\_D*, *PERC\_R*) represents the number of joining (departing, replaced) managers as a percentage of prior team size. These variables are interacted with the *EVENT* variable to test whether results differ by the significance of the turnover event. We continue not to find evidence that managerial turnover affects fund survival.

In summary, we find no evidence that manager-turnover events affect the subsequent survival of hedge funds. A potential reason is the lack of precision in the event dates, as described in Section 2.4.1.

## 2.5 *STAKE* and performance: why do teams underperform?

The hedge fund industry can serve as a laboratory to assess whether teams make better decisions than individuals. As mentioned, decision-making outcomes in this setting are relevant, observable, and quantified in the form of excess fund returns. Y. Chen et al. (2024) find that team-managed hedge funds (TMHs) underperform solo-managed hedge funds (SMHs). The authors attribute this underperformance to inferior decision-making abilities of teams.

However, the industry’s high proportion of fund managers with equity ownership may limit the external validity of these findings. The underperformance of TMHs could be due to conflicts arising from these equity ownerships, rather than from inherent flaws in team decision-making. Managers might differ in their risk appetite depending on the size of their personal equity ownership (*STAKE*) and their investment horizons. For instance, a stakeholding manager with a short investment horizon might prioritize short-term profits through performance fees over long-term gains from management fees. Supporting this idea, Gupta and Sachdeva (2022, Table A4) find that hedge funds run by firms with dispersed equity ownership perform worse, and they attribute this underperformance to potential firm-internal conflicts.

The findings of Y. Chen et al. (2024) and Gupta and Sachdeva (2022) may be related, as TMHs tend to exhibit higher ownership dispersion. Figure 2.5 illustrates this relationship by plotting the number of fund managers against the Herfindahl-Hirschman Index (HHI) of their equity stakes. The observed negative relationship between team size and equity concentration is not trivial, given the presence of both equity owners who are not managers and managers without equity. The negative relationship raises the question: does the underperformance of TMHs genuinely reflect an inferiority of team decision-making, or is it instead an artifact of conflicts of interest arising from diverse economic interests?

To investigate, we replicate the findings of Y. Chen et al. (2024) with additional controls for *STAKE*. We estimate the following pooled OLS regression:

$$\begin{aligned} PERFORMANCE_{i,t} = & \beta_1 TEAM_{i,t} + \beta_2 TEAM_{i,t} \times TSTAKE_{i,t} + \beta_3 TSTAKE_{i,t} \\ & + \sum_j \beta_4^j FUND\_CTRLS_{i,t}^j + \sum_k \beta_5^k YEAR\_FE_t^k + \sum_l \beta_6^l STYLE\_FE_i^l + \varepsilon_{i,t}, \end{aligned} \tag{2.7}$$

where *TEAM* is an indicator variable equal to 1 if a fund is managed by more than one PM, and 0

otherwise. *TSTAKE* represents the sum of all equity ownerships of the PMs in the team. For SMHs, *TSTAKE* is equal to *STAKE*. The dependent variable, *PERFORMANCE*, is measured as either average monthly style-adjusted returns (*SA12*) or average monthly Fung and Hsieh (2004) 7-factor alphas (*FH12*), each over 12-month periods. All variables are observed at annual intervals to avoid autocorrelation in the dependent variable.

Panel A of Table 2.7 reports the results. We first exclude the *TSTAKE* variables in Columns (1) and (2). In Column (1), the negative coefficient estimate for *TEAM* confirms the underperformance of TMHs, as documented by Y. Chen et al. (2024). Specifically, SMHs outperform THMs by 0.052% of style-adjusted return per month (0.47% per annum). In Column (2), we replace the binary variable *TEAM* with the cardinal variable *TEAMSIZ*E, which captures the number of team members, obtaining equivalent results. Columns (3) to (6) incorporate information about *STAKE*. In Column (3), the positive coefficient for *TSTAKE* suggests that fund performance improves with the total equity ownership of its managers. However, in Column (4), the negative coefficient for the interaction term  $TEAM \times TSTAKE$ , while insignificant, offsets the positive effect of *TSTAKE*, and the coefficient estimate for *TEAM* turns insignificant. The results weakly suggest that equity ownership is more beneficial for fund performance when the equity is owned by a single PM rather than by a team. To investigate further, Column (5) includes interaction terms between the *TEAM* variable and indicators for different ranges of *TSTAKE*. Specifically, we categorize all non-zero *TSTAKE* values into four quartiles, with breakpoints at 25%, 62.5%, and 90%, and include a dummy variable for each quartile ( $Q_1$  to  $Q_4$ ). Zero *TSTAKE* serves as a baseline. Consistent with the previous findings, we observe that the positive effect of *TSTAKE* increases with magnitude, partially offset by negative effects for the interactions between *TEAM* and the *TSTAKE* quartiles. As a robustness test, Column (6) repeats the analysis using Fung and Hsieh (2004) 7-factor alphas instead of style-adjusted returns (as in Y. Chen et al., 2024), producing equivalent results.

To summarize, the analysis indicates that hedge fund performance is influenced by both the management structure – whether the fund is managed by a solo PM or a team – and the equity ownership of the PMs. Firm equity ownership is beneficial for the performance of solo PMs. For teams, depending on the sample and performance measure used, the effect is less positive or even negative. If team members do not have equity, then team management yields equivalent or better results than solo management.

**Endogeneity** Endogeneity concerns are prevalent due to potential unobserved differences between funds. To address these concerns, Y. Chen et al. (2024) conduct difference-in-differences analyses on funds that transition from solo to team management (i.e., SMHs becoming TMHs), or vice versa. They identify 93 of such transitions. When analyzing the consequences of these changes, they focus on the 63 funds that switch from SMH to TMH; 38 of which have sufficient data.<sup>29</sup> Similarly, we identify 642 funds that switch between team and solo management, with 215 transitioning from SMH to TMH and 363 vice versa.<sup>30</sup> The remaining 64 funds transition multiple times. The decision to switch is endogenous, which is why a comparison with propensity-score-matched (PSM) peer funds would be appropriate (as in Y. Chen et al., 2024, Table 11). However, we find that even with our larger sample, the PSM-chosen peers – and therefore the results – depend significantly on the choice of factors in the PSM model.

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<sup>29</sup>Y. Chen et al. (2024, Table 10) use the prior-month return to predict transitions between solo- and team-management. The use of a single month's return to predict management changes may not fully capture the complexities of such decisions. Short-term returns are highly volatile and can be influenced by transient factors, arguably making them less reliable indicators of the performance relevant for managerial changes.

<sup>30</sup>Y. Chen et al. (2024) infer the events from manager-history data in the Morningstar Direct hedge fund database, which, while less numerous, may be more accurate than the data inferred from snapshots.

Instead, we estimate a regression similar to the previous one, with a focus on the 642 event funds. We use monthly instead of annual style-adjusted returns for better accuracy regarding the event times. In addition to year-month fixed effects, we also include fund fixed effects, which render the fund-specific time-invariant control factors obsolete. Although fund-specific time-varying factors might be partially offset by transitions occurring in both directions (SMHs to TMHs and vice versa), our analysis cannot fully control for these factors. The results, reported in Columns (1) and (2) of Panel B in Table 2.7, provide no evidence that these particular funds performed better or worse when they were TMHs. In the remaining Columns (3) to (6), we require Form ADV data, shrinking the sample to 151 funds (51 SMH to TMH transitions; 90 vice versa; 10 multiple transitions). In Columns (3) and (4), the economically and statistically significant coefficient estimates for *TEAM* and *TEAMSIZ*E suggest that this subsample may not be representative of the larger event sample used in Columns (1) and (2). Consistent with Panel A, the already positive effect of *TEAM* (in Column 3) increases after controlling for *TSTAKE* (in Column 6). In summary, this analysis of event funds provides weak confirmatory evidence that equity ownership is beneficial for SMHs but not for TMHs, and that the observed underperformance of TMHs is related to equity ownership.

**Robustness** As a robustness test, Panel C of Table 2.7 repeats the analysis of Panel A using Sample #2. The results are expected to be weaker given the smaller sample size and the lack of information on historical managers. Still, in line with Panel A, we observe that the negative effects of *TEAM* and *TEAMSIZ*E (Columns 1 and 2) disappear after controlling for the interaction between *TEAM* and *TSTAKE*. The effect of *TSTAKE* is generally positive, but not when the fund is managed by a team.

## 2.6 *SKIN*, domicile, and the flow-performance relationship

The flow-performance relationship is a well-documented phenomenon. Past fund performance predicts future fund flows – “money tracks performance” – for both mutual funds and hedge funds.<sup>31</sup> Previous studies suggest that the shape of the flow-performance relationship (FPR) – concave, linear, or convex – depends on asset liquidity. The equity capital of a hedge fund (its AUM) is fragile because it can be redeemed at the investors’ discretion. These investors have an incentive to redeem early if they anticipate that negative performance will trigger coordinated redemptions by other investors. Investors who do redeem early enjoy a first-mover advantage, as they can exit the fund before its cash holdings are exhausted and positions have to be liquidated to satisfy redemptions (Liu & Mello, 2011). Closing positions – selling longs or covering shorts – to generate cash or release margin capital has an adverse market impact on asset prices; this impact is more severe when assets are less liquid. Consequently, investors’ incentives to redeem early are stronger when liquidation costs due to asset illiquidity are higher.

Correspondingly, hedge funds with share restrictions exhibit a concave FPR, while those without exhibit a convex FPR (Liang et al., 2019). This is plausible, because, in the absence of a liquidity mismatch, hedge funds without share restrictions will hold more liquid assets.<sup>32</sup> The same relationships between the shape of the FPR and asset liquidity have been observed for mutual funds: while equity mutual funds exhibit a convex FPR (e.g., Sirri and Tufano, 1998), the relationship is concave for corporate

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<sup>31</sup>For mutual funds, see Chevalier and Ellison (1997) and Sirri and Tufano (1998). For hedge funds, see Agarwal et al. (2004), Baquero and Verbeek (2009, 2021), Fung et al. (2008), Getmansky (2012) and Goetzmann et al. (2003).

<sup>32</sup>For example, Q. Chen et al. (2010, Table 8) provide evidence that mutual funds with illiquid assets are more likely to impose redemption restrictions.

bond mutual funds (Goldstein et al., 2017). Even within equity and corporate bond mutual funds, those that hold more illiquid assets exhibit a stronger sensitivity of outflows to poor performance (Q. Chen et al., 2010; Goldstein et al., 2017).<sup>33</sup>

How does *SKIN* fit in? As discussed in the introduction to this chapter, insiders may signal to investors that they would be “holders of last resort” in case of a “run” on the fund’s assets, and thereby prevent the “run” in the first place. This phenomenon would be unique to hedge funds, because *SKIN* (as a percentage of AUM) is negligible in mutual funds. Gupta and Sachdeva (2022) find that funds with high *SKIN* indeed exhibit a weaker FPR, which they attribute to *SKIN* improving capital stability. However, a weaker FPR has also been observed for hedge funds domiciled in the United States (“onshore”), compared to those domiciled in the Cayman Islands or other “offshore” tax havens. Specifically, Aragon et al. (2014) argue that regulatory constraints – on fund marketing, investor types, and the maximum number of investors – make it more difficult to raise capital for onshore funds and thus weaken their FPR, especially for high-performing onshore funds.

These findings of Gupta and Sachdeva (2022) and Aragon et al. (2014) may be related, because fund managers at hedge fund firms are often US citizens with a tax-motivated preference to invest in “onshore” funds. Indeed, we find that feeder funds based in Delaware show a markedly higher average *SKIN* of 24.3%, compared to 9.1% for those domiciled in the Cayman Islands. This difference aligns with the fact that 92.7% of investors in Delaware feeders are US persons, while only 43.7% of investors in Cayman feeders are US persons.<sup>3435</sup>

So, is the weaker FPR of high-*SKIN* funds an artifact of their domicile, or vice versa? To investigate, we follow Aragon et al. (2014, Panel 6) and run separate regressions for onshore and offshore hedge funds. In each of these two regressions, we follow Gupta and Sachdeva (2022, Table VI) in regressing flows on the interaction between fund performance and an indicator variable that identifies funds with above-median *SKIN*. To avoid autocorrelation in the dependent variable, we observe variables at quarterly frequency, as in both Aragon et al. (2014) and Gupta and Sachdeva (2022):

$$\begin{aligned}
 FLOW3_{i,t+1} = & \beta_1 RANK\_CA12_{i,t} + \beta_2 RANK\_CA12_{i,t} \times INSIDER_{i,t} + \beta_3 INSIDER_{i,t} \\
 & + \sum_j \beta_4^j FUND\_CTRL_{i,t}^j + \sum_l \beta_5^k STYLE\_FE_i^k + \sum_m \beta_6^l YM\_FE_t^l + \varepsilon_{i,t}, \quad (2.8)
 \end{aligned}$$

where *FLOW3* are quarterly fund flows (flows over the past three months). We use CAPM alpha rank over the prior year (*RANK\_CA12*) to measure relative fund performance (Agarwal et al., 2018). The results are qualitatively unchanged if we instead follow Aragon et al. (2014) and measure performance as

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<sup>33</sup>In a hedge fund setting, Agarwal et al. (2019) find that funds of hedge funds (FoHFs) with a liquidity mismatch (defined as a redemption frequency that is lower than the value-weighted redemption frequencies of their underlying hedge fund investments) are subject to greater capital fragility than FoHFs without such a mismatch, because their investors have a stronger incentive to preemptively redeem capital in response to underperformance.

<sup>34</sup>Feeder funds are rarely domiciled in other jurisdictions than Delaware or the Cayman Islands. Of the 4,432 hedge fund feeders in our Form ADV dataset, 88% are domiciled in the Cayman Islands (49%) or Delaware (39%), followed by Ireland (3%), Bermuda (2%), and the British Virgin Islands (2%). The focus here is on feeder funds, because the master-fund data usually aggregates the feeder-fund information, as discussed before.

<sup>35</sup>Given their different investor bases, differences in FPR between offshore and onshore hedge funds could also stem from cultural norms. For example, standard narratives of cultural norms portray North American institutions as relatively impatient with underperformance, which on its own would suggest a *stronger* FPR for onshore funds. However, in a cross-country survey of institutional investors, Goyal et al. (2023) observe the opposite: North American respondents report longer holding periods than respondents from Europe or the rest of the world. In general, they find that culture is least important in manager selection.

relative style-adjusted performance. *INSIDER* is an indicator variable equal to 1 for observations with above-median *SKIN*, and 0 otherwise (as in Gupta and Sachdeva, 2022). *FUND\_CTRL* are fund-specific control variables. *STYLE\_FE* and *YM\_FE* are fixed effects for style and year-month, respectively.<sup>36</sup>

The results, reported in Columns (1) and (2) of Table 2.8, support both Gupta and Sachdeva (2022) and Aragon et al. (2014). Specifically, the coefficient estimate for *RANK\_CA12* is positive and significant for both onshore and offshore funds, confirming the general FPR. The coefficient is larger for offshore funds than for onshore funds, consistent with Aragon et al. (2014). The interaction between *RANK\_CA12* and *INSIDER* is negative, confirming Gupta and Sachdeva (2022). These results hold also when flows are calculated over longer periods in Columns (3) to (6). The FPR is weaker for onshore than for offshore funds, and *SKIN* further mitigates this relationship for both types of funds.

**Underlying mechanisms** According to Gupta and Sachdeva (2022), the weaker flow-performance relationship of *INSIDER* funds stems from (a) managers restricting the inflow of outsider capital into *INSIDER* funds, which causes lower inflows after good performance, and (b) insider capital being more resilient to underperformance, resulting in less severe outflows after bad performance. The authors empirically confirm that the flows of *INSIDER* funds respond less strongly to poor performance.<sup>37</sup> However, since only net flows are analyzed, these observed effects might alternatively result from (a) more outflows after positive performance or (b) more inflows after negative performance.

To investigate further, we differentiate between inflows and outflows. While only net flows can be derived from the AUM data provided by commercial vendors, empirical observations show that hedge funds with a quarterly redemption policy often choose the calendar quarter-ends – March-, June-, September-, and December-end – as their redemption dates. This phenomenon is corroborated by Figure 2.6, which contrasts the effect of monthly versus quarterly redemption frequencies on the volatility of fund flows by calendar month. Specifically, hedge funds permitting quarterly redemptions demonstrate higher flow volatility following the conclusion of a calendar quarter, coinciding with the period when redemptions are processed.

Thus, in order to separate inflows and outflows, we focus on hedge funds with quarterly redemption frequency. Such funds constitute 56% of all hedge funds in Sample #2 (36% allow for monthly redemptions). Any flows experienced by these funds outside of their quarterly redemption dates are likely inflows. To the best of our knowledge, we are the first to isolate inflows in this manner. We estimate the following regression to test whether *INSIDER* funds exhibit muted in- and outflows:

$$FLOW1_{i,t+1} = \beta_1 INSIDER_i \times QEND_t + \beta_2 INSIDER_i + \beta_3 QEND_t + \sum_j \beta_4^j FUND\_CTRL_{i,t}^j + \sum_k \beta_5^k STYLE\_FE_i^k + \sum_l \beta_6^l YEAR\_FE_t^l + \varepsilon_{i,t}. \quad (2.9)$$

<sup>36</sup>We chose Sample #2 for this analysis to ensure better replicability, and because the analysis does not require data on historical managers. Moreover, Sample #2 allows to retain duplicate fund vehicles, which we choose to do in this analysis, because we are interested in the differential effects of onshore and offshore domiciled vehicles. The results are robust to the removal of duplicate vehicles.

<sup>37</sup>Specifically, Gupta and Sachdeva (2022) isolate the effect of very negative (bottom-decile) returns on fund flows (see their Table VI, Specification 2). They observe that such poor returns have a less negative impact on flows in the case of *INSIDER* funds. This moderating effect is limited to returns in the prior quarter, that is, in the quarter immediately preceding the quarter for which flows are calculated. The effect is surprising, because redemption terms can make it impossible for investors to effectuate redemptions in such a timely fashion. For example, due to redemption notice periods (at least 30 days for a typical hedge fund), a redemption from a hedge fund with quarterly (or less frequent) redemption dates would affect flows only one quarter later.

$FLOW1_{i,t+1}$  are fund  $i$ 's flows over the following month  $t + 1$ . The variable of interest is the interaction between  $QEND$  and  $INSIDER$ .  $QEND$  indicates whether month  $t$  is a calendar quarter-end (March, June, September, or December). We naturally include year fixed effects instead of year-month fixed effects. The regression otherwise follows the prior analysis in Equation 2.8. The results reported in Columns (1) and (2) of Table 2.8 support Gupta and Sachdeva (2022): the interaction  $INSIDER \times QEND$  is positive and statistically significant. Both potential explanations corroborate the authors: either the outflows are relatively low (supporting the notion that  $SKIN$  improves capital stability) or the inflows are relatively low (supporting the notion that fund managers restrict the entry of outsiders).

In Columns (3) and (4), we estimate equivalent regressions for onshore versus offshore funds. Aragon et al. (2014, Footnote 9) predict that onshore hedge funds – like US mutual funds held by taxable investors (Bergstresser & Poterba, 2002) – experience lower inflows and lower outflows due to unrealized capital gains (“tax overhang”). In line with this prediction, we find the interaction between  $ONSHORE$  and  $QEND$  to be positive. The other distinguishing characteristics of onshore funds have partly opposing implications for the relative magnitude of inflows vis-à-vis outflows. Specifically, Aragon et al. (2014) argue that regulatory constraints hinder the ability of onshore funds to raise investor capital ( $\rightsquigarrow$  lower inflows; higher net outflows). To mitigate liquidity risks caused by the resulting inability to offset outflows with inflows, onshore funds pursue more liquid strategies ( $\rightsquigarrow$  lower net outflows) and employ more restrictive liquidity terms: longer lockup periods, higher minimum investment amounts, and less frequent redemption and subscription cycles ( $\rightsquigarrow$  lower inflows; lower net outflows).<sup>38</sup> The authors observe that (a) onshore funds’ flows respond significantly less strongly to positive performance, and (b) insignificantly more strongly to negative performance, both before (Panel B of Table 6) and after (Panel C) controlling for redemption terms. Given that (a) is the dominating effect, the observed positive interaction between  $ONSHORE$  and  $QEND$  aligns with these findings of Aragon et al. (2014).<sup>39</sup>

In Columns (5) and (6), we include both the  $INSIDER$  and  $ONSHORE$  variables in the same regressions, obtaining results equivalent to columns (1) to (4). In Columns (7) and (8), we run placebo tests of funds with monthly (instead of quarterly) redemption periods. As expected, the coefficient estimates for the  $QEND$  dummy are insignificant for these monthly funds, while they had been significantly negative in Columns (1) to (6). This is consistent with our argument that quarterly-redemption funds see worse net flows at calendar quarter-ends, because those quarter-ends tend to be the only times when redemptions are possible. The interactions with  $QEND$  are also insignificant, as expected. To summarize, both  $INSIDER$  and  $ONSHORE$  funds exhibit a weaker FPR. Focusing on hedge funds with quarterly redemption periods allows to distinguish between inflows and outflows. Doing so, we find further evidence in favor of Aragon et al. (2014) and Gupta and Sachdeva (2022) in that (a) the weaker FPR of  $INSIDER$  funds is caused by more muted inflows or outflows rather than by the existence of offsetting flows, and (b)  $ONSHORE$  funds exhibit more muted inflows and outflows as well, potentially due to “tax overhang” effects.

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<sup>38</sup>Interestingly, the more restrictive *subscription* terms (higher minimum initial investments and less frequent subscription dates) seem counter-intuitive in the narrative of Aragon et al. (2014). These terms, which make it harder for investors to provide capital, are puzzling choices because, according to the authors, onshore funds are smaller, struggle to raise capital, and invest in more liquid assets and strategies (where capital can be more easily deployed). The sole motivation would be to avoid classification as a publicly traded partnership (PTP).

<sup>39</sup>Gupta and Sachdeva (2022) include the redemption frequency to control for the possibility that redemption terms affect the FPR, but do not interact the variable with fund performance.

## 2.7 *SKIN* during the hedge fund life cycle

*SKIN* is the percentage of the fund owned by insiders. It is determined by in- and outflows of insider and outsider capital, as well as differences in the returns generated on these capital sources. Such differences can arise, for example, because insiders typically pay lower fees, if any. We investigate the factors affecting the evolution of *SKIN* over the lifetime of a fund.

**Relationship between *SKIN* and fund age** We begin by exploring relationships across funds to uncover broad patterns in the evolution of *SKIN*. Figure 2.7 presents cross-sectional binned scatter plots of *SKIN* against fund age (Panel A), *SKIN* against fund size (Panels B and C), and fund size against fund age (Panels D and E). Fund size is measured either by fund AUM (from commercial databases) or by the number of investors (from Form ADV). Panel A reveals a U-shaped relationship between fund age and *SKIN*. Intuitively, in the early years of a fund’s existence, fund managers invest a significant proportion of their own capital relative to the small initial AUM, resulting in high *SKIN* (Boyson, 2003). As the fund attracts external investments, *SKIN* decreases. More surprisingly, after this initial period, *SKIN* rises again, even though AUM does not decline with age (as shown in Panel D), potentially indicating a wealth transfer from outsiders to insiders.

Next, we investigate the relationship between *SKIN* and fund age at the fund level. We model this relationship as V-shaped using a piecewise linear function. To control for time-invariant fund-specific factors, we first obtain the residuals from a regression of *SKIN* on fund fixed effects. We then estimate a segmented regression model of these residuals on fund age to identify the breakpoint – the low point of the “V” – in the relationship between fund age and *SKIN*. The model identifies the breakpoint at 6.34 years of fund age ( $t = 29.64$ ,  $p < 0.01$ ). The initial segment has a negative slope estimate of  $-0.62$  ( $t = -11.34$ ,  $p < 0.01$ ). At the breakpoint, the slope increases by 0.78 ( $t = 13.99$ ,  $p < 0.01$ ), resulting in a new, positive slope of 0.15.

We confirm these findings in Column (1) of Table 2.9. Here, we regress the monthly level of *SKIN* on the variables *FAGE\_BEF* and *FAGE\_AFT*, which represent the piecewise linear components of fund age around the breakpoint at 6.34 years. For observations where fund age is less than the breakpoint, *FAGE\_BEF* is equal to fund age, and *FAGE\_AFT* is set to 0. For observations where fund age is greater than or equal to the breakpoint, *FAGE\_BEF* is set to the breakpoint value, and *FAGE\_AFT* is equal to fund age minus the breakpoint. Column (1) confirms the segmented (V-shaped) relationship, with the coefficient estimates for *FAGE\_BEF* and *FAGE\_AFT* displaying the expected signs. In the first 6.34 years, before the breakpoint, *SKIN* decreases by 1.39% per year since fund launch. After the breakpoint, it increases by 1.02% per year. Both slopes are steeper than those estimated in the segmented regression; this difference arises because the slopes are now estimated simultaneously with the fixed effects.

Column (2) provides consistent evidence of a non-linear relationship between fund age and *SKIN* by including a quadratic term for fund age. The negative coefficient for the linear term and the positive coefficient for the quadratic term are consistent with a U-shaped relationship. Specifically, the coefficients ( $-0.45$  for the linear term and  $0.04$  for the quadratic term) imply a decrease in *SKIN* until 5.26 years of fund age, which is close to the 6.34 years estimated from the segmented regression. Notably, while the models in Columns (1) and (2) shed light on contemporaneous correlations between *SKIN* and fund age, they are silent on causation. Error terms are serially correlated due to the autocorrelation of *SKIN*, which is why we focus our interpretation on the magnitude of the coefficient estimates.

**Factors determining the evolution of *SKIN*** In Columns (3) to (7) of Table 2.9, we use quarterly changes in *SKIN* as the dependent variable. All variables are observed at quarterly intervals to approximately align with the 121-day median delay between Form ADV filings. The regression in Column (3) is specified as follows:

$$\begin{aligned} \Delta SKIN\_QLY_{i,t} = & \beta_1 FAGE_{i,t} + \beta_2 \log(AUM_{i,t-1}) + \beta_3 FLOW3_{i,t} + \beta_4 \Delta NINV_{i,t} \\ & + \beta_5 SKIN_{i,t-1} + \beta_6 RETQ_{i,t-1} + \beta_7 RETQ_{i,t} + \beta_8 TEAMSIZ E_{i,t} \\ & + \sum_j \beta_9^j FUND\_FE_t^j + \sum_j \beta_{10}^k YQ\_FE_t^k, \end{aligned} \quad (2.10)$$

where  $\Delta SKIN\_QLY_{i,t}$  are changes in *SKIN* of fund  $i$  in quarter  $t$ . We categorize potential determinants into three areas: (a) outsider flows, (b) insider flows, and (c) differences in returns generated on insider versus outsider capital. To investigate (a), we include quarterly fund flows (*FLOW3*) and quarterly changes in the number of fund investors ( $\Delta NINV$ ). As expected, both coefficients are negative and significant. Specifically, in Column (3), an additional investor reduces *SKIN* in the same quarter by 0.027%, and a 1% inflow reduces *SKIN* by 0.013%.

For (b), first, the negative coefficient for the level of *SKIN* indicates mean reversion behavior: if insider investment was unusually high or low in the previous quarter, insiders might adjust their investment in the following quarter to bring it back toward a more typical level. Second, we test whether *SKIN* changes are positively associated with fund returns. Performance-fee income after positive fund returns may increase the ability and willingness of insiders to provide capital. Insiders may also be obligated (implicitly or explicitly) to reinvest performance-fee income.<sup>40</sup> In line with these hypotheses, we find that better fund performance in the prior quarter ( $RETQ(t-1)$ ) leads to more positive *SKIN* changes in the subsequent quarter. However, the economic magnitude is minor: a 1 percentage-point higher quarterly return is associated with a subsequent 0.007% increase in *SKIN*. Third, in Column (4), we add the number of team members (*TEAMSIZ E*) and the team's cumulative equity ownership (*TSTAKE*) as covariates, speculating that solo or stakeholding managers might be more inclined to bet their *SKIN*, because they have more control over investment decisions. However, we find no significant effects.

For (c), we include same-quarter returns ( $RETQ$ ). In the absence of insider or outsider flows, *SKIN* is expected to increase because insiders pay lower fees. Due to performance fees, this difference in appreciation between insider and outsider capital should increase with fund returns.<sup>41</sup> The coefficient estimates for  $RETQ$  have the expected positive sign but are statistically and economically insignificant.<sup>42</sup>

For both (b) and (c), we include management and incentive fees in Column (5). Fund fixed effects

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<sup>40</sup>For example, the estimation of managerial incentives in Agarwal et al. (2009) is based on the assumption, grounded in insights from industry practitioners, that performance fees are *entirely* reinvested.

<sup>41</sup>For performance fees to apply, the fund's NAV must be above the high-water mark (if applicable), which may be investor specific (Ackermann et al., 1999, Footnote 11), and fund returns may have to exceed a hurdle rate. However, 83% of funds in our sample do not have a hurdle rate, and investors take little advantage of their high-water marks (Ben-David et al., 2023).

<sup>42</sup>A potential reason for the lack of significance is that the effect may be limited to positive fund returns. Theoretically, the impact of lower insider performance fees is symmetric: (1) if the fund return is positive and performance fees accrue, then insider capital benefits from the lower performance fee and appreciates more strongly than outsider capital; (2) if the fund return is negative, then any accrued but not yet crystallized performance fees are reversed, resulting in relatively better *outsider* returns. (Even in scenario (2), insider capital may still achieve a better return due to the management fee and other factors, but this would not affect the coefficient estimate of  $RETQ$ .) However, Elaut et al. (2015, Figure 1) show that 89% of CTAs in TASS have a crystallization frequency of quarterly or higher. Assuming hedge funds follow this pattern, then scenario (2) would not apply, because performance fees crystallize each quarter and thus can never be reversed.

are removed because fees are time-invariant in our sample. *SKIN* changes are expected to be positively associated with fees, as higher fees likely increase insider wealth and widen the gap between insider and outsider fees. Indeed, we find that a 1 percentage-point increase in the management fee (e.g., from 1% to 2% per annum) is associated with 0.23% higher quarterly changes in *SKIN*. A 10 percentage-point increase in the performance fee (e.g., from 10% to 20% per annum) is associated with 0.19% higher quarterly changes. In Columns (6) and (7), we estimate separate regressions for the two periods before and after the breakpoint at 6.34 years. The positive effect of management fees is driven by the post-breakpoint period (Column 7), during which we expect managers to reinvest fee income.

To summarize, we document a non-linear relationship between fund age and insider ownership (*SKIN*). Initially, *SKIN* decreases, presumably due to the influx of external capital. After an average of 6.34 years, *SKIN* increases as the growth in insider capital outpaces that of outsider capital. Inflows of outsider capital, measured by net flows or increases in the number of investors, naturally reduce *SKIN*. *SKIN* exhibits mean reversion, possibly because insiders target a certain *SKIN* level. Fund returns and subsequent-quarter *SKIN* changes are weakly positively related, reflecting insiders' increased ability or willingness to invest after strong performance. Finally, *SKIN* changes are more positive when fees are higher, which is expected since higher fees should increase insider wealth (*cet. par.*) and are likely to widen the gap between insider and outsider fees.

## 2.8 Hedge fund leverage and risk

The Form ADV data allows us to infer hedge fund leverage. Specifically, Gross Asset Value (GAV) from Form ADV filings can be divided by AUM from commercial databases to estimate gross leverage. We use this leverage estimate to revisit relationships between fund leverage and fund risk.

Using Form PF filings, Barth et al. (2020) investigate the relationship between hedge fund leverage and risk. Their main finding is a weak negative correlation between leverage and fund risk, which they attribute to a strong negative correlation between leverage and asset risk (i.e., the risk of the individual securities in the fund portfolio). These findings are consistent with theories of leverage constraints, according to which market participants overpay for high-risk assets to compensate for a lack of access to leverage (Black, 1972; Boguth & Simutin, 2018; Frazzini & Pedersen, 2014; Garleanu & Pedersen, 2011).

Barth et al. (2020) calculate asset risk as the volatility of asset returns, among other risk measures. Crucially, to obtain these asset returns, the authors divide fund returns by gross leverage ( $GAV/AUM$ ). Using Sample #2, Panel A of Figure 2.8 replicates Figure 4 in Barth et al. (2020).<sup>43</sup> It shows a binscatter plot of average gross leverage against the standard deviation of "asset returns" ( $R \times AUM/GAV$ ). The plot exhibits the expected negative relationship. However, dividing fund returns by gross leverage to calculate asset returns can be problematic. When a hedge fund has both long and short positions, fund returns may not scale linearly with gross leverage, as they would for long-only or short-only funds.<sup>44</sup> To illustrate, consider two funds, A and B, each with USD 10 million in AUM:

- Fund A is a long-only hedge fund with 150% long leverage (i.e., USD 15 million invested in long

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<sup>43</sup>We use Sample #2 for this section because the data on net and gross leverage limits is exclusive to EurekaHedge, and because the section does not require data on historical managers.

<sup>44</sup>One exception, though unrealistic, would be a long-short fund in which the short securities are perfectly negatively correlated with the long securities.

securities) and 0% short leverage.

- Fund B is a long-short hedge fund with 150% long leverage and 50% short leverage (i.e., USD 5 million worth of securities sold short).
- All securities earn a 6% return.<sup>45</sup>

Fund A, which returns 9%, would be correctly assigned an “asset return” of 6% ( $= 9\%/150\%$ ). However, Fund B, which returns 6% ( $= 150\% \times 6\% - 50\% \times 6\%$ ), would be assigned an asset return of just 3% ( $= 6\%/200\%$ ). Thus, even though the actual asset returns are identical for both funds, they are estimated to be lower for Fund B. If fund returns do not scale linearly with gross leverage due to the presence of both long and short positions, dividing fund returns by gross leverage will not accurately reflect asset returns. As the authors note, gross leverage will overstate the actual risk whenever any of the short positions hedge long positions (or vice versa). The underestimation of asset returns becomes more severe as gross leverage increases if the unhedged exposure (1) is a stronger driver of risk and return than the hedged exposure, and (2) does not increase at least proportionally with gross leverage. Both conditions (1) and (2) are intuitively expected to hold. Panels B and C of Figure 2.8 examine these conditions using four static data fields from the EurekaHedge database. These fields contain each fund’s self-reported minimum and maximum levels of net and gross leverage.<sup>46</sup>

Regarding (1), we use net leverage as a proxy for unhedged exposure to examine the relationship between gross leverage ( $GAV/AUM$ ), unhedged exposure, and risk across funds. We begin by separating funds into two groups based on whether their minimum (or maximum) net leverage is above or below the median of 20% (or 80%). We then further segment the dataset by gross-leverage deciles and calculate the return volatility for each combination of gross-leverage decile and net-leverage group. Panel B of Figure 2.8 visualizes the results. In the left-hand chart, within each gross-leverage decile, risk (as measured by return volatility) is higher for funds with above-median minimum net leverage than for funds with below-median minimum net leverage. The right-hand chart shows equivalent results for maximum net leverage. These findings suggest that unhedged exposure (proxied by net leverage) is a stronger driver of risk than hedged exposure.

Regarding (2), if funds increase their unhedged exposure with gross leverage, then we would expect to see a positive relationship between a fund’s gross and net leverage limits. However, Panel C of Figure 2.8 provides no evidence that funds with higher gross-leverage limits allow themselves higher net-leverage limits. Instead, funds with low maximum gross leverage tend to have higher minimum net leverage. To generate returns, such “long-biased” hedge funds may rely on unhedged, directional risk rather than on spread risks. If the underestimation of asset returns indeed becomes more severe with increasing leverage, then this underestimation can lead to a spurious negative correlation between leverage and asset return volatility, as observed in Panel A of Figure 2.8. Underestimating asset return volatility can also cause asset betas to be underestimated, since the covariance with factor returns is likely to be lower due to this underestimation.

In conclusion, this method of calculating asset returns – dividing fund returns by gross leverage – can create an illusion of reduced volatility with higher leverage, which does not accurately reflect the true risk profile of the fund’s assets.<sup>47</sup> Determining the asset returns of long-short funds is complex and requires

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<sup>45</sup>For simplicity, costs and other frictions are ignored for this illustration.

<sup>46</sup>These data fields have also been used in Section 1.7.

<sup>47</sup>Numerous factors aside from asset returns influence the relationship between gross leverage and fund returns. Specifically,

additional information, such as position-level data (e.g., from Form 13F) or long and short leverage data (e.g., from Form PF).

## 2.9 Conclusion

We combine historical versions of three hedge fund databases to obtain information on portfolio manager careers. Using Form ADV data, we add time-varying variables on fund, firm, and manager level, in particular: each manager’s firm equity ownership (*STAKE*) and ability to exercise firm control (*CONTROL*), the amount of insider investment in a fund (*SKIN*), and the Gross Asset Value (GAV) of the fund portfolio. We document five findings.

First, hedge fund managers are predominantly entrepreneurs rather than employees: 65% of managers own a *STAKE* and 62% exercise *CONTROL* at least once during their tenure at a firm. Consistent with managerial entrenchment and career concerns, owning *STAKE* or exercising *CONTROL* lowers the probability that a manager departs from a fund. In line with the notion that hedge fund managers tend to depart voluntarily because their position within the firm exempts them from potential termination, we find no evidence that these departures are preceded by underperformance. These stylized facts are generally in contrast to the mutual-fund industry, where terminations are used as an “internal governance” device (Dangl et al., 2006). Consequently, when managers are immune to getting fired the responsibility for performance evaluation falls more heavily on the investors. Akin to investors in small mutual fund families, hedge fund investors may need to compensate by strengthening the flow-performance relationship as a form of external governance (Bessler et al., 2018).

Second, while *STAKE* should align the incentives of managers and investors, it can also lead to firm-internal conflicts when ownership is shared among several partners. We relate the findings of Gupta and Sachdeva (2022) on the underperformance of hedge funds operated by firms with dispersed equity ownerships to those of Y. Chen et al. (2024) on the underperformance of hedge funds managed by teams of portfolio managers compared to solo-managed hedge funds. We find that the underperformance of teams disappears once we control for the cumulative *STAKE* of the team members, suggesting that equity ownership can exacerbate coordination problems and internal conflicts. *STAKE* is beneficial for the performance of solo managers, but for teams, depending on the sample and performance measure, the effect is less positive or even negative. Analyzing hedge funds that transition between solo and team management, we continue to find no evidence that team management leads to underperformance.

Third, we show that the weaker flow-performance relationship of hedge funds with high *SKIN* (Gupta & Sachdeva, 2022) is not due to the fact that such high-*SKIN* hedge funds tend to be domiciled in the US (“onshore”) (Aragon et al., 2014), or vice versa. Instead, both factors – *SKIN* and onshore domiciliation – weaken the flow-performance relationship. In an additional test, we differentiate between inflows and outflows by analyzing monthly flows of hedge funds with quarterly redemption frequency. In line with the underlying mechanisms proposed by Aragon et al. (2014) and Gupta and Sachdeva (2022), both high-*SKIN* and onshore hedge funds exhibit muted in- and outflows.

Fourth, hedge fund managers seem to reinvest significantly in their funds, creating a U-shaped

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higher-leveraged funds – even when compared to strategy peers – might be more diversified, employ more sophisticated risk management techniques, incur higher borrowing costs to achieve leverage, or face stricter regulation. Additionally, reverse causality could introduce a selection bias, where only funds with certain characteristics, such as managerial skill or pedigree, are able to take on higher leverage.

relationship between *SKIN* and fund age and leading to *SKIN* being significantly higher for hedge funds than has been observed for mutual funds. Changes in *SKIN* are more positive when fund fees are higher, which is consistent with the notion that higher fees increase insider wealth and that insider capital is charged lower fees. *SKIN* changes are also weakly positively related to fund returns in the prior period, indicating greater ability or willingness to reinvest after positive performance.

Finally, fund returns scale differently with gross leverage, depending on the relative magnitudes of long and short leverage. Therefore, we caution against methodologies that infer asset returns by dividing fund returns by gross leverage.

Regarding data quality, we observe that database changes provide only vague information about real-world events. Managerial departures and hires are reflected in Form ADV data a median of 134 days and 275 days earlier, respectively, than in the database snapshots. Aware of these limitations, we focus on analyses that do not require precise event dates. Future research could follow us in identifying hedge fund managers involved in turnover events from historical databases, but then infer the event dates from Form ADV filings, rather than from the databases. This would likely reduce the sample size but also improve the accuracy of the event dates.

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## Figures

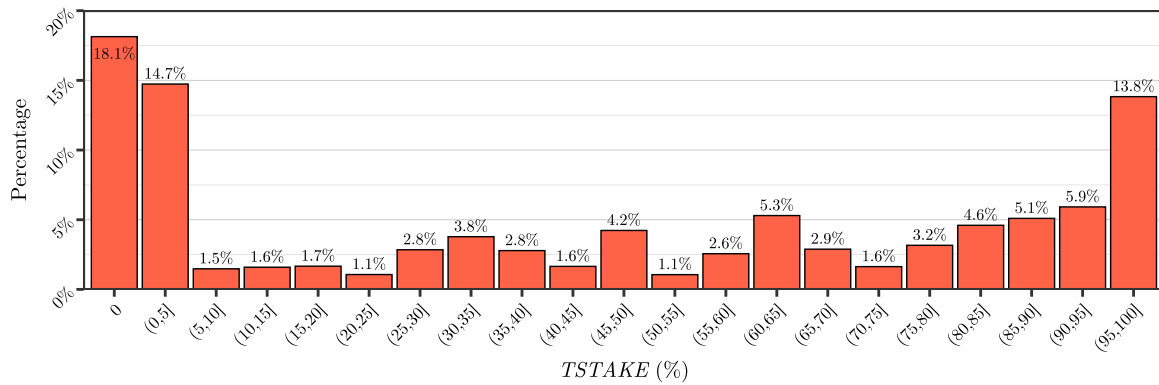
**Figure 2.1:** Master-fund aggregation in Form ADV data



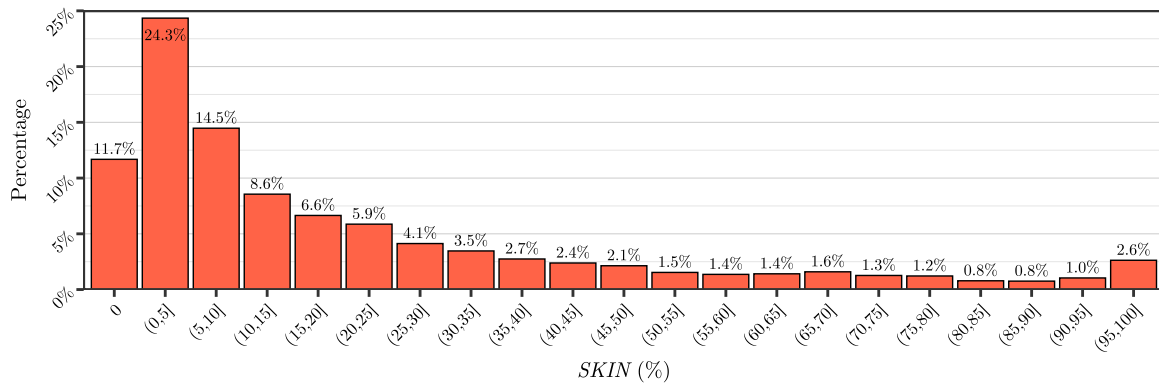
*Note.* This figure presents a quantile-to-quantile comparison between the number of investors in a master fund and the sum of investors across its feeder funds. Combinations where the sum of investors in the feeder funds exceeds the number in the master fund are highlighted in red. In these cases, the number reported at master-fund level is apparently not an aggregation of the feeder-fund numbers. The dataset includes information on 2,089 master hedge funds and 3,569 feeder hedge funds, derived from Form ADV Schedule D filings submitted between December 2011 and December 2023. The number of investors is sourced from Section 7.B.(1), Question 13 of Form ADV, which asks for the “approximate number of the private fund’s beneficial owners”.

**Figure 2.2:** Distribution of *TSTAKE* and *SKIN*

**Panel A:** Distribution of management-team ownership (*TSTAKE*)

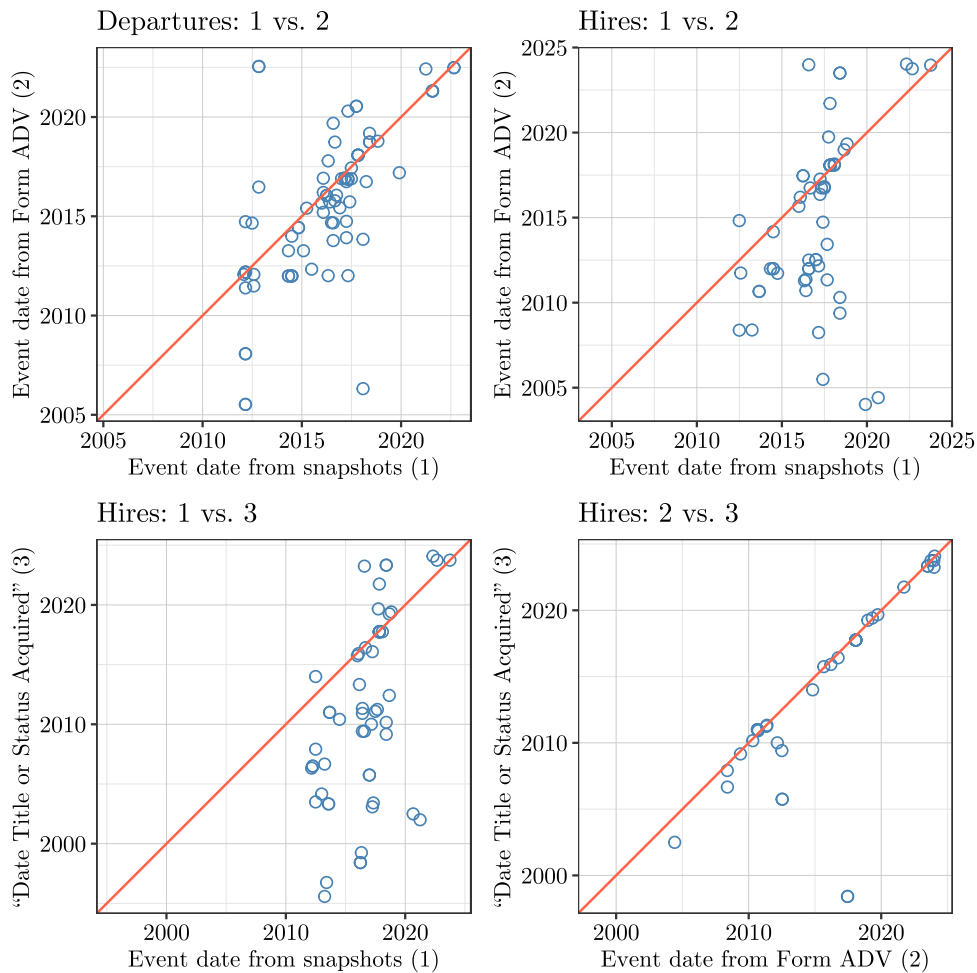


**Panel B:** Distribution of insider investment (*SKIN*)



*Note.* Using Sample #1, the figure depicts the distribution of managerial firm ownership (*TSTAKE*) and insider investment (*SKIN*). *TSTAKE* is the total equity ownership of all portfolio managers of a hedge fund. *SKIN* is the percentage of fund AUM owned by all “related persons”, as defined by the SEC.

**Figure 2.3:** Data quality: comparison of turnover event dates from different sources

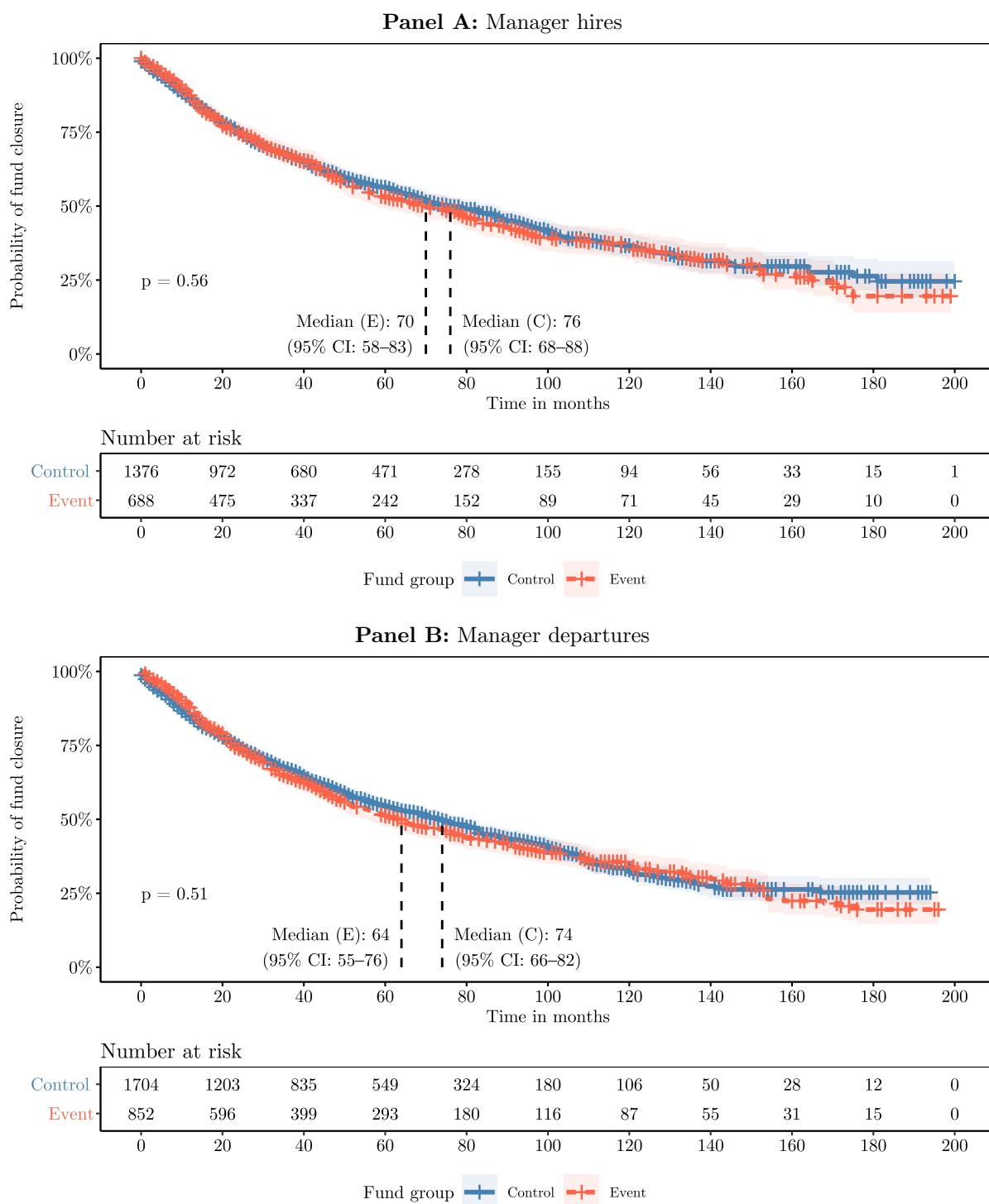


*Note.* Using Sample #1, the figure compares the dates of managerial turnover events (hires and departures) inferred from three different sources:

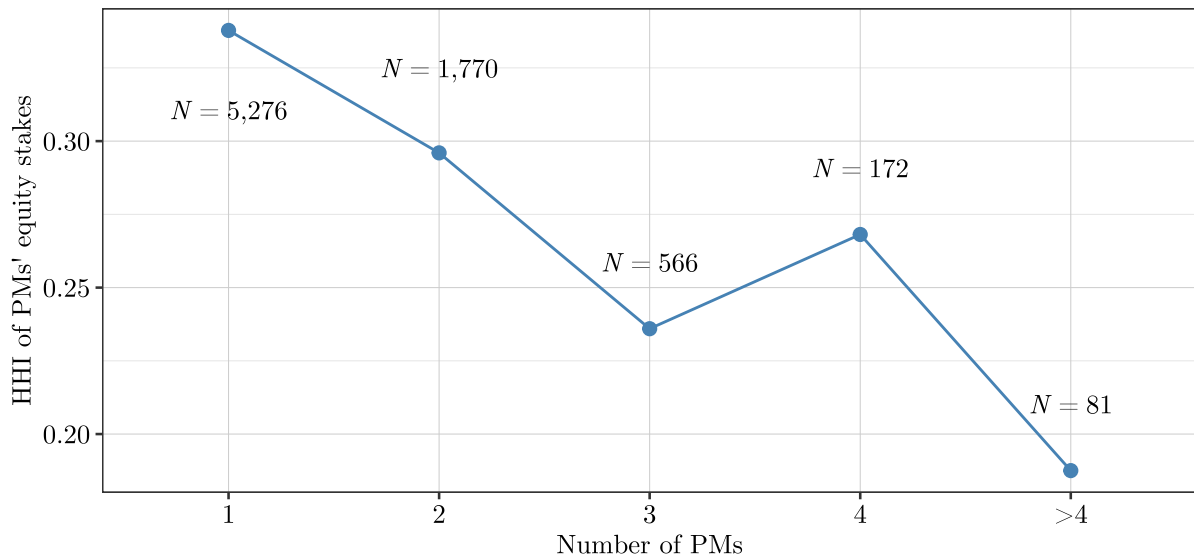
1. Historical snapshots of commercial hedge fund databases: turnover events (hires and departures) are identified at the fund level by detecting changes in the fund-manager-name data field between consecutive snapshots.
2. Comparison of Form ADV filings: turnover events (hires and departures) are identified at the firm level by comparing the names listed in Schedule A across consecutive Form ADV filings of a firm.
3. “Date Title or Status Acquired MM/YYYY” data field in Form ADV Schedule A: turnover event dates (hires only) are identified directly from the “Date Title or Status Acquired MM/YYYY” data field for each person listed in Schedule A.

In the first row, the left-hand chart compares sources 1 and 2 with regard to departures, while the right-hand chart compares the same sources with regard to hires. In the second row, the left-hand chart compares sources 1 and 3, and the right-hand chart compares sources 2 and 3.

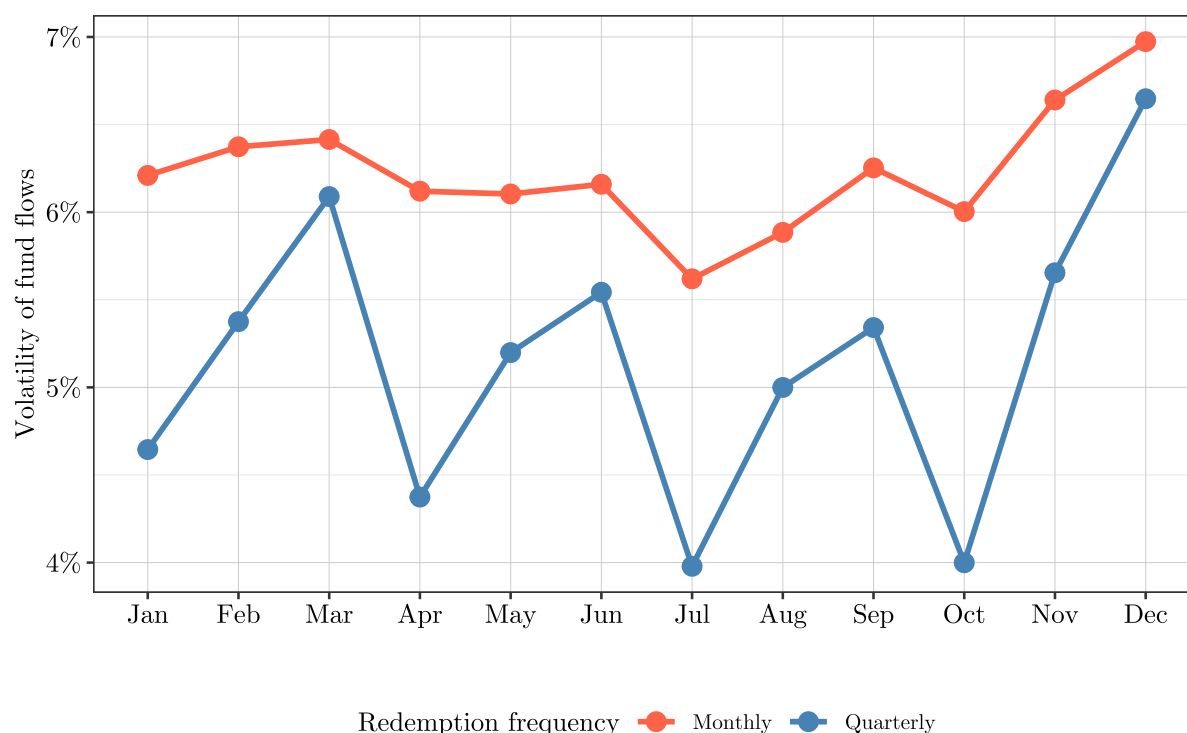
**Figure 2.4:** Survival times of hedge funds post managerial turnover



*Note.* Using Sample #1, the figure presents Kaplan-Meier plots of the (right-censored) remaining survival times of hedge funds following a portfolio-manager hire (Panel A) or departure (Panel B). The “event” group includes hedge funds that experience the respective manager turnover event. Each fund in the “event” group is matched with two “control” funds based on their propensity for liquidation at the time of the event. The survival curves indicate the percentage of funds still active (not closed) over time. Vertical lines highlight the median survival times of each group, with 95% confidence intervals shown in brackets.

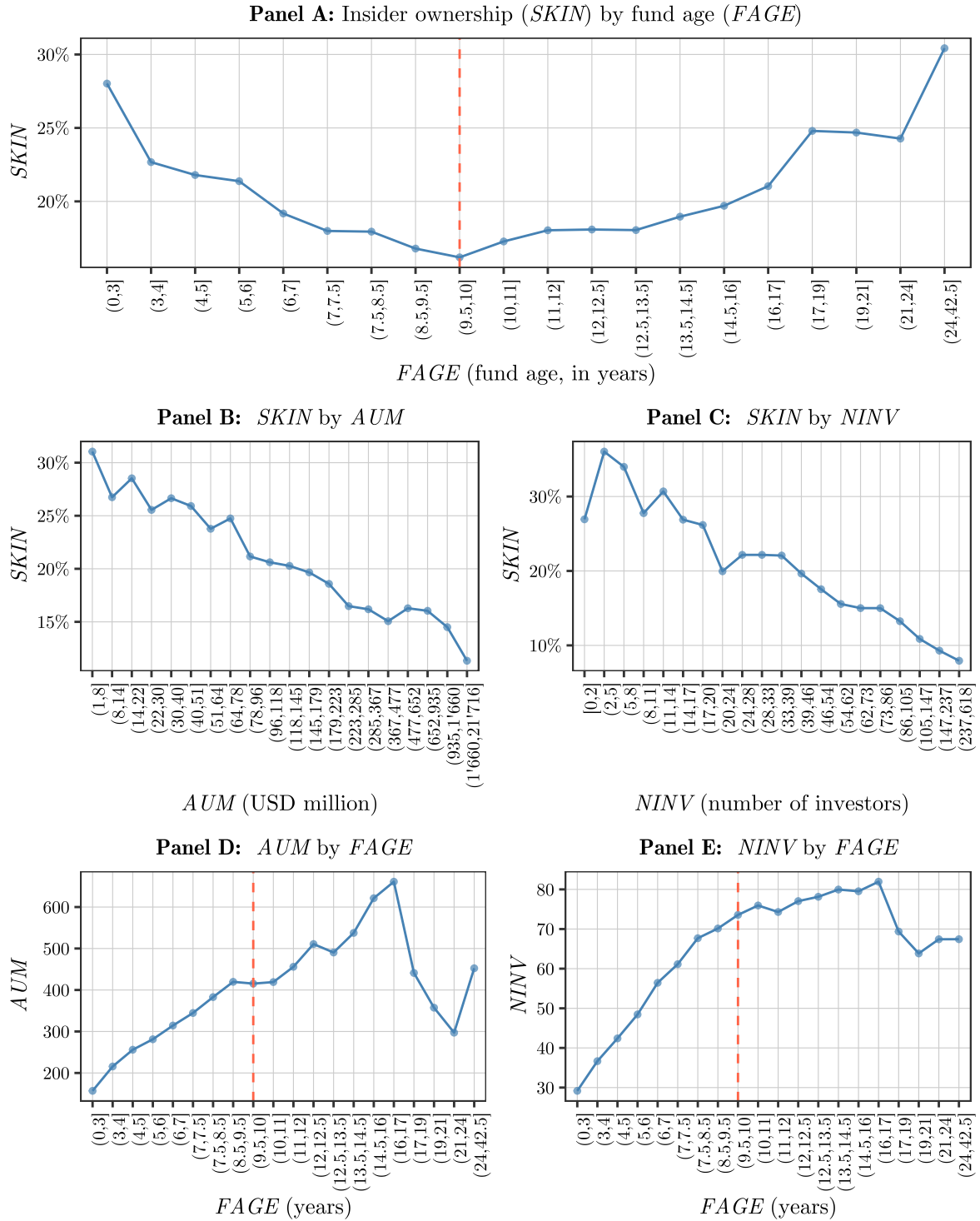
**Figure 2.5:** Number of hedge fund managers versus equity ownership concentration

*Note.* Using Sample #1, the figure illustrates the negative relationship between the number of portfolio managers of a hedge fund and the Herfindahl–Hirschman Index (HHI) of their equity stakes (*STAKE*). The sample includes 7,865 annual observations from December 2011 to December 2023 for the 1,570 hedge funds in Sample #1 with available data.

**Figure 2.6:** Volatility of monthly hedge fund flows by fund redemption frequency

*Note.* Using Sample #2, this figure illustrates that the variability of hedge fund flows within a calendar month depends on the funds' redemption frequency. The x-axis lists the calendar months, while the y-axis quantifies the variability of net fund flows, measured as the standard deviation. For each combination of fund and month, at least six flow observations are required to calculate a standard deviation of flows. The chart shows two lines representing the mean standard deviations for two distinct groups of hedge funds: those offering monthly redemptions and those with quarterly redemptions. The sample comprises 1,203 funds with monthly redemption frequency and 662 funds with quarterly redemption frequency. All funds have monthly subscription periods and are USD denominated.

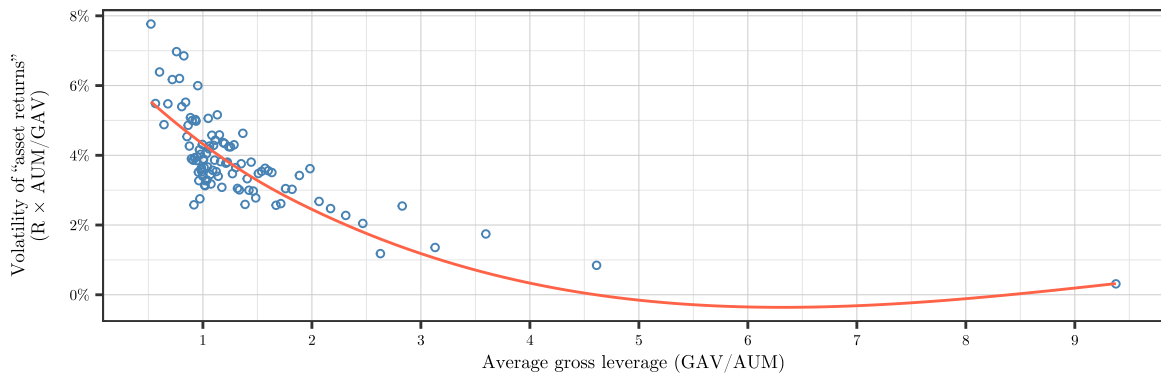
Figure 2.7: *SKIN* during the hedge fund life cycle



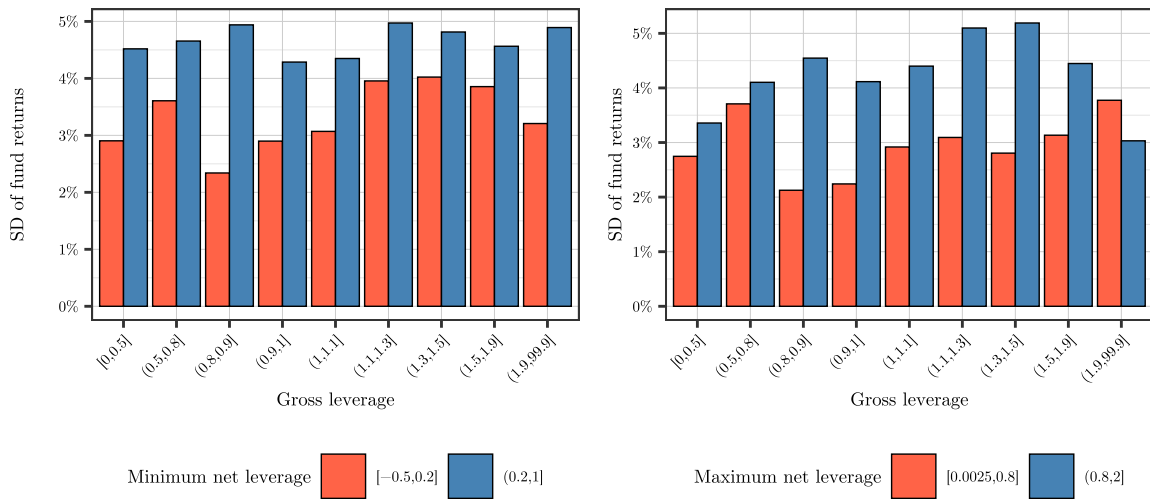
Note. Using Sample #1, the figure presents five binscatter plots of insider investment (*SKIN*) against fund age *FAGE* (Panel A), *SKIN* against fund AUM (*AUM*) (Panel B), *SKIN* against the number of investors (*NINV*) (Panel C), *AUM* against *FAGE* (Panel D), and *NINV* against *FAGE*, respectively. In each plot, the y-axis displays the average of the respective variable calculated for each bin.

**Figure 2.8:** Hedge fund leverage versus fund risk

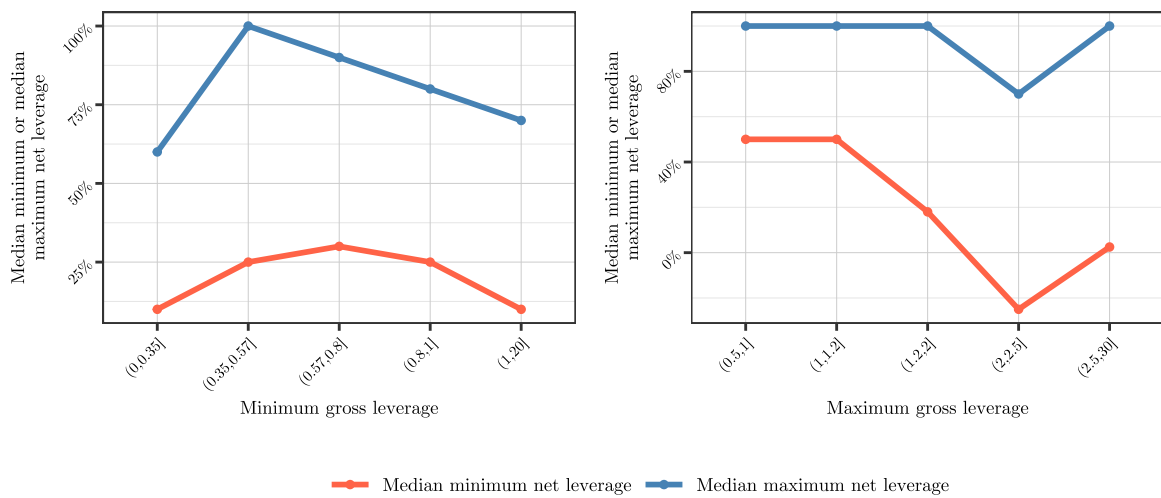
**Panel A:** Estimated asset-return volatility vs. leverage



**Panel B:** Effect of net and gross leverage on fund returns



**Panel C:** Relationship between net- and gross-leverage limits of hedge funds



*Note.* Using Sample #2, this figure follows the methodology of Barth et al. (2020) to investigate the relationship between hedge fund leverage and asset risk (Panel A), and highlights potential limitations of that methodology (Panels B and C).

- Panel A replicates the top panel of Barth et al. (2020, Figure 6). It presents a binscatter plot that examines the relationship between gross leverage and the standard deviation of “asset returns” (returns divided by gross leverage as in Barth et al., 2020). Gross-leverage values are pooled across funds and sorted into 50 quantiles. The average gross leverage of each quantile is then plotted against the volatility of its “asset returns”. Gross leverage is calculated as the Gross Asset Value (GAV) of the fund divided by its AUM. Observations with gross leverage below 50% are excluded.
- Panel B examines the relationship between gross leverage (GAV/AUM), net-leverage limits, and risk. The left-hand chart shows the standard deviation of fund returns across nine gross-leverage quantiles. In each quantile, funds with minimum net leverage above and below the median (20%) are compared. The right-hand chart follows the same approach but groups funds by maximum net leverage, with a median of 80%.
- Panel C compares net- and gross-leverage limits. The left-hand plot sorts funds into quintiles by minimum gross leverage, and displays the median minimum (red) and maximum (blue) net leverage for each quintile. The right-hand plot does the same for maximum gross leverage. Funds with maximum gross leverage below 50% are excluded.

Panels A, B, and C include observations for the 327, 347, and 1,411 hedge funds in Sample#2 with available data, respectively. Panels A and B cover the period from December 2011 to December 2023, and Panel C is time-independent.

## Tables

**Table 2.1:** Availability of database snapshots

This table summarizes the availability of historical versions (“snapshots”) of the EurekaHedge, HedgeFund.net (HFN), and TASS databases. These snapshots are used in Sample #1 to track changes in fund management teams. For each year and database, the table reports the number of months with at least one snapshot from the respective provider. The EurekaHedge database is divided into six (partially overlapping) groups: hedge funds from Asia, Emerging Markets, Europe, Latin America, and North America, as well as UCITS-compliant hedge funds.

Year / Provider	EurekaHedge						HFN	TASS	Total
	AHF	EMHF	EHF	LAHF	NAHF	UCITS			
2007 (from April)	6	6	—	6	—	—	8	9	35
2008	5	4	—	5	—	—	12	12	38
2009	8	8	—	7	—	—	12	12	47
2010	9	9	—	9	—	—	12	12	51
2011	10	10	—	10	—	1	11	12	54
2012	12	12	—	12	—	12	—	12	60
2013	10	10	—	10	—	10	—	11	51
2014	10	10	—	10	—	10	—	9	49
2015	11	11	3	11	1	11	—	12	60
2016	12	12	12	12	12	12	—	12	84
2017	10	10	10	10	11	10	—	10	71
2018	8	8	8	8	8	8	—	8	56
2019	1	1	1	1	1	1	—	9	15
2020	—	—	—	—	—	—	—	7	7
2021	6	6	6	6	6	6	—	9	45
2022	11	11	11	11	11	11	—	11	77
2023	12	12	12	12	12	12	—	12	84
2024 (January)	1	1	1	1	1	1	—	1	7
Total	142	141	64	141	63	105	55	180	891

**Table 2.2:** Summary statistics of Sample #1

*Note.* The table summarizes Sample #1, which consists of data for 5,274 USD-denominated hedge funds from May 2005 to December 2023. A “person” or “team” refers to any unique combination of a portfolio manager (PM) or portfolio-management team and firm.

- Groups I and II: *FEMALE* indicates if the PM is female, determined using prefixes, the *genderize.io* API, or manual assignment. *MAGE* (manager age) is estimated using the *agify.io* API, based on first names and locations, and truncated at 18 years. *TEAMSIZ*E is the number of PMs in a team.
- Group III: *AUM* are fund assets under management, in USD million. *FAGE* is the fund’s age since inception, in years. *NAPPR* refers to the number of times a fund appears in the snapshots sample. A fund might have multiple appearances due to duplicate share classes or inclusion in multiple databases. *NSNAP* is the number of database snapshots available for the month (max. 3). For the six sub-databases within EurekaHedge, each category is counted as 1/6 of a snapshot. *RET* are monthly net (after-fee) fund returns, here reported in percent for presentation purposes. *STAGNANT* is true if an *AUM* data point remains unchanged for three consecutive months despite positive or negative fund returns. *UNION* indicates whether *RET* or *AUM* for a given fund-date combination is taken from the UNION dataset (instead of EurekaHedge, TASS, or HFN).
- Group IV: This group includes *AVGAUM* (average *AUM* over the period a fund is observed), *BIG4* (1 if the fund’s financial statements are audited by Deloitte, EY, KPMG, or PWC), *DEAD* (1 if the fund stopped reporting to the databases), *ILLIQ* (first-order autocorrelation of *RET*, a measure of portfolio illiquidity, Getmansky et al., 2004), *HWM* (1 if the fund has a high-water mark), *IFEE* (incentive fee p.a.), *MFEE* (management fee p.a.), *MININV* (minimum initial investment, USD million), *LEVERED* (1 if levered), *LOCKUP* (1 if a lockup exists), and *REST* (redemption restriction period: *REDFREQ* (redemption frequency) + *REDNOTI* (redemption notice period) in days, Agarwal et al., 2024). Statistics for fund-closure and inception dates (*DEATH\_DATE* and *INCEPTION\_DATE*) are calculated using a sequential count of year-months, which is then converted back into calendar dates.
- Groups V to VII (Form ADV variables): *CONTROL* and *STAKE* are derived from Schedule A/B, where *CONTROL* indicates whether the PM is a “Control Person”. *STAKE* and *TSTAKE* represent the equity ownership of individual PMs and teams, respectively. The variables in group VII are taken from Schedule D Section 7.B.(1) “Private Fund Reporting”, specifically questions 6. (a) “Is this a ‘master fund’ in a master-feeder arrangement?” (*MASTER*); 6. (c) “Is this a ‘feeder fund’ in a master-feeder arrangement?” (*FEEDER*); 11. “Current gross asset value of the private fund” (*GAV*; in USD million); 12. “Minimum investment commitment required of an investor in the private fund” (*MININV\_ADV*; in USD million); 13. “Approximate number of the private fund’s beneficial owners” (*NINV*); 14. “What is the approximate percentage of the private fund beneficially owned by you and your related persons” (*SKIN*); 15. (a) “What is the approximate percentage of the private fund beneficially owned (in the aggregate) by funds of funds” (*PERC\_OW\_N\_FOF*); and 16. “What is the approximate percentage of the private fund beneficially owned by non-United States persons” (*PERC\_OW\_N\_INT*). The uneven minimum value for *NINV* is caused by interpolation, and the unusual maximum value for *MININV\_ADV* (USD 59,608,198) is reported as such.

	Number of...	Number of observations		Min.	Median	Mean	Max.
		Total	Observed				
<i>Commercial hedge fund data (May 2005 to December 2023)</i>							
<i>I. Manager variables</i>	<i>...persons</i>						
<i>FEMALE</i>	8,756	8,756	100.0%	0.000	0.000	0.068	1.000
<i>MAGE</i>	8,756	8,756	99.6%	18.000	59.000	58.270	85.000
<i>II. Team variables</i>	<i>...teams</i>						
<i>TEAMSIZE</i>	6,813	331,875	100.0%	1.000	1.000	1.441	9.000
<i>III. Fund variables</i>	<i>...funds</i>						
<i>AUM</i>	5,274	331,875	85.3%	0.231	53.920	291.051	44,100.000
<i>FAGE</i>	5,274	331,875	100.0%	0.083	8.000	9.284	46.833
<i>NAPPR</i>	5,274	331,875	100.0%	0.000	1.000	1.131	27.000
<i>NSNAP</i>	5,274	331,875	100.0%	0.000	2.000	1.711	2.500
<i>RET (%)</i>	5,274	331,875	91.8%	-100.000	0.370	0.311	220.278
<i>STAGNANT</i>	5,274	331,875	100.0%	0.000	0.000	0.039	1.000
<i>UNION</i>	5,274	331,875	100.0%	0.000	0.000	0.293	1.000
<i>IV. Fund characteristics</i>	<i>...funds</i>						
<i>AVGAUM</i>	5,274	5,274	100.0%	0.898	52.895	241.080	32,493.697
<i>BIG4</i>	5,274	5,274	100.0%	0.000	1.000	0.685	1.000
<i>DEAD</i>	5,274	5,274	100.0%	0.000	1.000	0.726	1.000
<i>HWM</i>	5,274	5,274	99.6%	0.000	1.000	0.824	1.000
<i>IFEE</i>	5,274	5,274	99.5%	0.000	0.200	0.173	0.500
<i>ILLIQ</i>	5,274	5,274	100.0%	-0.578	0.080	0.088	0.890
<i>LEVERED</i>	5,274	5,274	98.9%	0.000	1.000	0.652	1.000
<i>LOCKUP</i>	5,274	5,274	99.5%	0.000	0.000	0.251	1.000
<i>MFEE</i>	5,274	5,274	99.7%	0.000	0.015	0.015	0.100
<i>MININV</i>	5,274	5,274	99.3%	0.000	0.500	1.186	50.000
<i>REST</i>	5,274	5,274	97.7%	1.000	60.000	88.128	1,110.000
<i>- REDFREQ</i>	5,274	5,274	98.9%	1.000	30.000	53.545	1,080.000
<i>- REDNOTI</i>	5,274	5,274	98.2%	0.000	30.000	34.142	365.000
<i>INCEPTION_DATE</i>	5,274	5,274	100.0%	Jan-67	May-06	Feb-06	Apr-20
<i>DEATH_DATE</i>	5,274	5,274	72.6%	Apr-07	Aug-15	Jan-15	Sep-23
<i>Form ADV data (December 2011 to December 2023)</i>							
<i>V. Manager variables</i>	<i>...persons</i>						
<i>CONTROL</i>	3,303	207,543	65.7%	0.000	1.000	0.665	1.000
<i>STAKE</i>	3,303	207,543	65.7%	0.000	0.138	0.307	1.000
<i>VI. Team variables</i>	<i>...teams</i>						
<i>TSTAKE</i>	2,512	141,506	65.2%	0.000	0.463	0.454	1.000
<i>VII. Fund variables</i>	<i>...funds</i>						
<i>FEEDER</i>	2,094	171,330	42.7%	0.000	0.000	0.020	1.000
<i>GAV</i>	2,094	171,330	42.7%	1.183	132.493	661.581	12,876.668
<i>MASTER</i>	2,094	171,330	42.7%	0.000	1.000	0.526	1.000
<i>MININV_ADV</i>	2,094	171,330	42.7%	0.000	0.500	1.102	59.608
<i>NINV</i>	2,094	171,330	42.7%	0.500	33.000	64.435	618.000
<i>PERC_OWNS_FOF</i>	2,094	171,330	42.7%	0.000	0.010	0.112	1.000
<i>PERC_OWNS_INT</i>	2,094	171,330	42.7%	0.000	0.317	0.410	1.000
<i>SKIN</i>	2,094	171,330	42.7%	0.000	0.100	0.210	1.000

**Table 2.3:** Firm ownership (*STAKE*) and control (*CONTROL*) among demographic groups

*Note.* Using Sample #1, this table presents the average *STAKE* and the proportion of individuals with *CONTROL* across different demographic groups of portfolio managers. Data for *STAKE* and *CONTROL* are derived from Form ADV Schedule A/B filings. For each combination of individual and firm, the most recent observation is used. Averages are calculated and reported for each demographic group; *t*-statistics for mean differences are shown in brackets.

Group	Average <i>STAKE</i>	Average <i>CONTROL</i>	<i>N</i>
Sex	Female (F)	0.194	165
	Male (M)	0.261	2,518
	Difference (F – M)	–0.067*** (–2.726)	–0.135*** (–3.374)
Age	<45 years (Y)	0.220	752
	≥ 45 and < 55 years	0.257	779
	≥ 55 and < 65 years	0.271	780
	≥ 65 years (O)	0.295	360
	Difference (Y – O)	–0.076*** (–3.443)	–0.112*** (–3.573)

**Table 2.4:** Patterns of manager changes

*Note.* Using Sample #1, the table summarizes the number of portfolio-manager (PM) changes observed within the sample period 2007-2023 by their effect on team size (Panel A) and by event type (Panel B).

**Panel A:** Number of events by their effect on team size

Before / after	1	2	3	4	5	>5	Total
1	356	189	27	6	3	2	583
2	303	101	50	6	—	—	460
3	59	98	31	28	3	—	219
4	10	3	35	8	3	3	62
5	3	5	3	13	3	2	29
>5	—	2	1	3	2	4	12
Total	731	398	147	64	14	11	1,365

**Panel B:** Number of events by type, source, fund style, and manager characteristics

	Portfolio manager...		Total
	...is hired	...departs	
<i>AUM range</i>			
AUM < USD 10mn	193	134	327
USD 10mn ≤ AUM < USD 25mn	228	166	394
USD 25mn ≤ AUM < USD 50mn	183	181	364
USD 50mn ≤ AUM < USD 100mn	221	151	372
USD 100mn ≤ AUM < USD 250mn	196	149	345
USD 250mn ≤ AUM < USD 500mn	136	122	258
USD 500mn ≤ AUM < USD 1bn	55	55	110
USD 1bn ≤ AUM	57	39	96
No AUM data	57	45	102
<i>Investment style</i>			
Credit	188	148	336
Macro	156	119	275
Managed Futures / CTA	103	59	162
Multi-Strategy	92	66	158
Relative Value	104	91	195
Other or not specified	36	37	73
<i>Provider</i>			
EurekaHedge	807	644	1,451
HedgeFund.net	266	247	513
TASS	294	195	489
<i>CONTROL</i>			
YES	82	68	150
NO	194	138	332
No data	1,050	836	1,886
<i>STAKE &gt; 0</i>			
YES	87	76	163
NO	189	130	319
No data	1,050	836	1,886
Total	1,326	1,042	2,368

**Table 2.5:** Determinants of portfolio-manager changes

*Note.* Using Sample #1, the table studies the determinants of portfolio-manager changes within a multinomial logistic regression framework. Panels A and B analyze on manager and fund level, respectively. In Panel A, the three possible event outcomes are the hire of a manager (“PM hire”), the departure of a manager (“PM departure”), and the closure of the fund (“Fund death”). In Panel B, the four possible event outcomes are the hire of at least one manager without a simultaneous departure (“PM addition”), the departure of at least one manager without a simultaneous hire (“PM exit”), the combination of manager hires and departures (“PM replacement”), and the closure of the fund (“Fund death”). In both panels, *SA12* and *SD12* represent the average monthly style-adjusted returns and the standard deviation of monthly returns over the prior 12 months, respectively. *FLOW12* represents the percentage AUM flows over the prior 12 months. *TEAMSIZE* denotes the size of the management team before the event. The remaining variables, detailed in the notes accompanying Table 2.2, are either observed at the time of the event or are time-invariant. All regressions include fixed effects for fund style and calendar year. All variables are observed at annual intervals, and explanatory variables are standardized to have unit variance. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Manager-level regressions

	Base outcome: no event					
	Dec. 2011 to Dec. 2023 (incl. Form ADV)			Apr. 2007 to Dec. 2023 (excl. Form ADV)		
	PM hire	PM departure	Fund death	PM hire	PM departure	Fund death
<i>STAKE</i>	-0.536*** (-3.516)	-0.482*** (-3.212)	0.070 (1.190)			
<i>CONTROL</i>	-1.022*** (-4.648)	-1.191*** (-5.864)	-0.633*** (-5.395)			
<i>SA12</i>	0.170** (2.133)	0.143* (1.888)	-0.444*** (-10.073)	0.032 (0.936)	0.003 (0.091)	-0.430*** (-18.842)
<i>SD12</i>	0.156** (1.968)	0.170** (2.271)	-0.032 (-0.697)	-0.007 (-0.182)	0.021 (0.615)	-0.150*** (-5.788)
<i>FLOW12</i>	-0.121 (-1.463)	-0.145* (-1.904)	-0.698*** (-8.582)	-0.081** (-2.247)	-0.100*** (-2.944)	-0.433*** (-12.329)
log( <i>AUM</i> )	-0.061 (-0.684)	-0.121 (-1.530)	-0.536*** (-10.558)	-0.083** (-2.049)	-0.138*** (-3.708)	-0.565*** (-22.298)
<i>TEAMSIZE</i>	-0.387*** (-4.009)	0.253*** (4.076)	-0.010 (-0.206)	-0.324*** (-7.159)	0.331*** (12.216)	0.018 (0.800)
<i>FEMALE</i>	0.294 (0.990)	0.420* (1.773)	-0.419** (-2.019)	0.418*** (3.261)	0.578*** (5.231)	-0.089 (-0.955)
<i>MAGE</i>	0.048 (0.591)	0.115* (1.647)	-0.016 (-0.369)	-0.166*** (-4.330)	-0.069** (-1.960)	0.018 (0.792)
<i>FAGE</i>	-0.280*** (-2.673)	-0.138 (-1.527)	-0.289*** (-5.435)	-0.081* (-1.726)	-0.154*** (-3.535)	-0.217*** (-8.312)
<i>MFEE</i>	0.063 (0.756)	-0.006 (-0.084)	0.016 (0.336)	0.042 (1.110)	0.085** (2.415)	-0.005 (-0.202)
<i>IFEE</i>	0.010 (0.089)	0.188* (1.904)	0.149** (2.406)	-0.086* (-1.804)	-0.056 (-1.252)	0.168*** (5.809)
log( <i>MININV</i> )	-0.168** (-2.202)	-0.060 (-0.877)	0.140*** (2.839)	0.062 (1.496)	0.063* (1.672)	0.226*** (8.376)
<i>LOCKUP</i>	0.001 (0.008)	0.091 (1.055)	-0.012 (-0.253)	-0.108** (-2.556)	-0.061 (-1.544)	-0.031 (-1.377)
log( <i>REST</i> )	0.037 (0.377)	-0.156* (-1.847)	0.036 (0.646)	-0.166*** (-3.491)	-0.094** (-2.123)	-0.003 (-0.105)
<i>LEVERED</i>	0.074 (0.880)	-0.055 (-0.775)	0.078* (1.737)	0.012 (0.319)	-0.061* (-1.790)	0.019 (0.888)
<i>HWM</i>	-0.047 (-0.472)	-0.065 (-0.727)	-0.033 (-0.591)	0.009 (0.214)	-0.004 (-0.105)	-0.039 (-1.511)
<i>NSNAP</i>	1.755*** (3.885)	1.371*** (4.233)	-0.153*** (-2.842)	1.292*** (9.301)	1.108*** (9.155)	-0.081** (-2.531)
<i>NAPPR</i>	0.078 (1.003)	0.101 (1.406)	-0.182*** (-2.734)	0.282*** (9.644)	0.303*** (10.869)	-0.068** (-2.371)
FE (year, style)	Yes			Yes		
Observations	8,868			28,091		
Number of events	172	236	681	822	1,011	2,830
Pseudo $R^2$	0.160			0.107		

Panel B: Fund-level regressions

	Base outcome: no event							
	Dec. 2011 to Dec. 2023 (incl. Form ADV)				Apr. 2007 to Dec. 2023 (excl. Form ADV)			
	PM addition	PM exit	PM replacem.	Fund death	PM addition	PM exit	PM replacem.	Fund death
<i>SA12</i>	0.241 (1.330)	-0.046 (-0.260)	0.302** (2.476)	-0.341*** (-5.735)	0.054 (0.693)	0.071 (1.212)	0.011 (0.256)	-0.413*** (-15.288)
<i>SD12</i>	0.236 (1.629)	-0.026 (-0.135)	-0.209 (-1.312)	-0.027 (-0.415)	-0.134 (-1.390)	-0.027 (-0.425)	0.057 (1.293)	-0.112*** (-3.715)
<i>FLOW12</i>	0.068 (0.408)	-0.054 (-0.287)	-0.452*** (-2.631)	-0.611*** (-5.933)	-0.034 (-0.494)	-0.012 (-0.233)	-0.119** (-2.411)	-0.469*** (-11.029)
log( <i>AUM</i> )	0.121 (0.617)	-0.103 (-0.641)	-0.061 (-0.453)	-0.454*** (-6.637)	0.128 (1.599)	-0.167** (-2.562)	-0.117** (-2.230)	-0.530*** (-17.622)
<i>TEAMSIZE</i>	0.303** (2.298)	0.782*** (9.485)	0.193* (1.763)	-0.044 (-0.679)	0.044 (0.589)	0.780*** (21.948)	0.154*** (3.563)	-0.006 (-0.206)
<i>FAGE</i>	0.172 (0.882)	0.305* (1.895)	-0.340** (-2.197)	-0.239*** (-3.564)	-0.060 (-0.627)	-0.117 (-1.567)	-0.160** (-2.540)	-0.206*** (-6.707)
<i>MFEE</i>	0.181 (1.020)	-0.138 (-0.933)	0.144 (1.115)	0.018 (0.297)	0.009 (0.110)	0.030 (0.492)	0.047 (0.964)	0.020 (0.752)
<i>IFEE</i>	-0.169 (-0.966)	0.353* (1.919)	0.060 (0.404)	0.129* (1.725)	-0.122 (-1.246)	0.093 (1.163)	-0.075 (-1.275)	0.130*** (3.965)
log( <i>MININV</i> )	-0.174 (-0.894)	-0.001 (-0.004)	-0.247* (-1.935)	0.280*** (4.129)	0.050 (0.551)	0.059 (0.874)	0.052 (0.996)	0.210*** (6.697)
<i>LOCKUP</i>	-0.400* (-1.713)	-0.150 (-0.864)	0.069 (0.540)	-0.013 (-0.215)	-0.098 (-1.180)	-0.032 (-0.463)	-0.116** (-2.084)	-0.040 (-1.484)
log( <i>REST</i> )	0.126 (0.629)	-0.418*** (-3.040)	-0.071 (-0.534)	0.016 (0.214)	-0.007 (-0.068)	-0.076 (-0.982)	-0.157*** (-2.591)	0.016 (0.479)
<i>LEVERED</i>	0.050 (0.269)	-0.177 (-1.190)	0.028 (0.228)	0.027 (0.449)	0.041 (0.524)	-0.069 (-1.129)	0.008 (0.158)	0.014 (0.544)
<i>HWM</i>	-0.107 (-0.578)	0.210 (1.118)	0.025 (0.174)	-0.075 (-1.139)	0.097 (1.019)	-0.002 (-0.024)	0.010 (0.176)	-0.037 (-1.256)
<i>NSNAP</i>	3.543 (1.196)	2.287*** (2.736)	2.496*** (3.116)	-0.211* (-1.859)	1.583*** (3.847)	1.466*** (4.987)	1.581*** (6.543)	-0.092 (-1.624)
<i>NAPPR</i>	0.048 (0.402)	0.154** (1.993)	-0.102 (-0.869)	-0.035 (-0.554)	0.293*** (6.306)	0.351*** (8.933)	0.265*** (7.570)	-0.056* (-1.753)
<i>SKIN</i>	-0.781** (-2.151)	0.100 (0.656)	0.129 (1.181)	0.129** (2.380)				
FE (year, style)	Yes				Yes			
Observations	4,941				18,911			
Number of events	34	58	80	352	188	344	489	1,994
Pseudo $R^2$	0.142				0.116			

**Table 2.6:** Fund survival after manager events

*Note.* Using Sample #1, the table explores the impact of managerial turnover on fund survival.

- Panel A examines the determinants of fund closure using binary logit regressions. The dependent variable, *DEATH*, equals 1 if a fund stops reporting (for reasons other than a merger or split) and 0 otherwise. *R12* (*R24*) is the average monthly fund return over the past 12 (24) months, while *S12* (*S24*) is the return standard deviation over the same period. The other independent variables are detailed in the notes to Table 2.2. To allow comparison, the same sample is used across all regressions. “Observations (available)” refers to the number of observations if only the variables in that column were required. Standard errors clustered by fund and year-month. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. The model in Column (5) of Panel A is used for a 2-to-1 propensity-score-matching procedure, where hedge funds that experience managerial turnover are matched to control funds that exhibit a similar likelihood of *DEATH* as the event funds at the time of turnover.
- Panel B evaluates the success of this matching process by comparing the means of the selected variables between control and event funds. Standard deviations are shown in brackets. The *p*-values indicate whether the differences between the groups are statistically significant.
- Using the sample of control and event funds from Panel A, Panel C reports the results of Cox proportional hazards models, testing whether managerial turnover affects the survival probability of hedge funds. The analysis is an alternative to the Kaplan-Meier plots presented in Figure 2.4. The dependent variable is the (right-censored) number of months in the remaining lifespan of each hedge fund. The indicator variable *EVENT* equals 1 if the hedge fund experiences the particular event, and 0 otherwise. Standard errors are clustered at the fund level. The table displays the hazard ratio for each explanatory variable, with Wald statistics shown in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.
- For Panel D, the analysis in Panels A to C is repeated on the fund level rather than on the individual-manager level. As in Panel B of Table 2.5, the three turnover events are the hire of at least one manager without a simultaneous departure (“PM addition”), the departure of at least one manager without a simultaneous hire (“PM exit”), and the combination of manager hires and departures (“PM replacement”). In specifications II, IV, and VI, the variable *PERC\_J* (*PERC\_D*, *PERC\_R*) represents the number of joining (departing, replaced) managers as a percentage of prior team size. These variables are interacted with the *EVENT* variable to test whether results differ by the significance of the turnover event. Otherwise, the regressions follow Panel C. In particular, the fund controls, omitted for brevity, are the same as in Panel C (*R12*, ...,  $\log(\text{REST})$ ).

**Panel A:** Logit regressions for fund closure propensity score estimation

	Dependent variable: <i>DEATH</i> (TRUE/FALSE)					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>R12</i>	-24.778*** (-10.469)		-24.552*** (-10.821)	-24.543*** (-10.800)	-24.420*** (-10.725)	-24.245*** (-10.627)
<i>R24</i>		-39.393*** (-12.652)				
<i>S12</i>	-5.232*** (-3.481)		-5.680*** (-4.080)	-5.630*** (-4.050)	-5.559*** (-4.021)	-5.798*** (-4.167)
<i>S24</i>		-6.140*** (-3.971)				
<i>FAGE</i>	-0.050*** (-9.145)	-0.050*** (-9.166)	-0.046*** (-9.051)	-0.045*** (-8.944)	-0.045*** (-8.961)	-0.045*** (-8.751)
$\log(AUM)$	-0.326*** (-15.744)	-0.323*** (-15.439)	-0.317*** (-15.352)	-0.318*** (-15.405)	-0.352*** (-16.728)	-0.365*** (-16.207)
<i>FLOW12</i>	-0.594*** (-5.620)	-0.483*** (-4.988)	-0.574*** (-5.494)	-0.573*** (-5.510)	-0.582*** (-5.512)	-0.576*** (-5.401)
Constant			-2.656*** (-25.664)	-2.803*** (-22.978)	-2.585*** (-24.672)	-2.886*** (-21.983)
<i>LEVERED</i>				0.100* (1.942)		
<i>HWM</i>				0.091 (1.374)		
<i>STAGNANT</i>					0.880*** (8.839)	0.875*** (8.752)
<i>BIG4</i>						0.171*** (2.914)
$\log(REST)$						0.059*** (3.128)
FE (year, style)	Yes	Yes	No	No	No	No
Observations (used)	199,582	199,582	199,582	199,582	199,582	199,582
Observations (available)	226,367	203,801	226,367	224,394	226,367	222,806
Squared Cor.	0.008	0.008	0.007	0.007	0.008	0.008
Pseudo $R^2$	0.054	0.055	0.050	0.050	0.053	0.054
BIC	21,819.00	21,794.60	21,634.00	21,651.10	21,558.90	21,560.80

**Panel B:** Quality of matching results

Event:	Departures			Hires		
	CONTROL	EVENT	Diff. ( $p$ )	CONTROL	EVENT	Diff. ( $p$ )
<i>R12</i>	0.003 (0.018)	0.004 (0.019)	0.189	0.003 (0.016)	0.005 (0.018)	0.053
<i>S12</i>	0.037 (0.032)	0.038 (0.034)	0.399	0.036 (0.032)	0.038 (0.036)	0.332
<i>FAGE</i>	9.717 (6.315)	8.076 (5.331)	< 0.001	9.759 (6.407)	8.057 (5.055)	< 0.001
$\log(AUM)$	4.275 (1.543)	4.347 (1.487)	0.263	4.303 (1.547)	4.397 (1.495)	0.185
<i>FLOW12</i>	0.058 (0.643)	0.047 (0.721)	0.695	0.098 (0.726)	0.053 (0.727)	0.184
<i>STAGNANT</i>	98 (5.751)	56 (6.573)	0.463	79 (5.741)	43 (6.250)	0.717
Observations	1,704	852		1,376	688	

**Panel C:** Cox proportional hazards regressions – on manager level

	Dependent variable: Survival time (months)			
	<i>EVENT</i> = PM hire		<i>EVENT</i> = PM departure	
	I	II	III	IV
<i>EVENT</i>	0.039 (0.657)	0.026 (0.354)	0.039 (0.589)	0.001 (0.014)
<i>R12</i>		-8.666*** (-4.504)		-8.457*** (-3.720)
<i>S12</i>		-4.276*** (-3.435)		-5.145*** (-3.542)
<i>FAGE</i>		-0.030*** (-3.859)		-0.037*** (-4.408)
log( <i>AUM</i> )		-0.168*** (-6.424)		-0.173*** (-6.028)
<i>FLOW12</i>		-0.145** (-2.507)		-0.115** (-2.247)
<i>LEVERED</i>		0.121 (1.583)		0.018 (0.219)
<i>HWM</i>		0.049 (0.417)		0.033 (0.281)
<i>STAGNANT</i>		-0.036 (-0.261)		0.322** (2.293)
<i>BIG4</i>		0.082 (0.924)		0.060 (0.608)
log( <i>REST</i> )		0.051* (1.901)		0.039 (1.355)
Number of deaths	1,249	1,221	984	961
Number of observations	2,556	2,497	2,064	2,017

**Panel D:** Cox proportional hazards regressions – on fund level

	Dependent variable: Survival time (months)					
	<i>EVENT</i> = PM addition		<i>EVENT</i> = PM exit		<i>EVENT</i> = PM replacement	
	I	II	III	IV	V	VI
<i>EVENT</i>	-0.179 (-1.260)		0.036 (0.359)		0.081 (0.891)	
<i>EVENT</i> × <i>PERC_J</i>		0.020 (0.183)				
<i>EVENT</i> × <i>PERC_D</i>				0.113 (0.549)		
<i>EVENT</i> × <i>PERC_R</i>						0.098 (0.918)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of deaths	268	268	527	527	724	724
Number of observations	558	558	1,031	1,031	1,488	1,488

**Table 2.7:** Effect of *STAKE* and team size on performance

*Note.* Using Samples #1 (Panels A and B) and #2 (Panel C), the table studies the interplay of team size and team equity ownership on fund performance. It reports the results of linear regressions on hedge fund performance. *TEAM* is an indicator variable equal to 1 if a fund is managed by more than one portfolio manager (PM), and 0 otherwise. *TEAMSIZ*E is the number of PMs within a team, and *TSTAKE* is their total equity ownership. In all panels, the dependent variables are expressed as percentages (i.e., multiplied by 100) to facilitate interpretation of the coefficients; *t*-statistics (in parentheses) are based on standard errors clustered by fund and year-month. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

- Panel A reports the main results. In Columns (1) to (5), performance is measured as average monthly style-adjusted returns over the past 12 months (*SA12*), while in Column (6), it is measured as average monthly Fung and Hsieh (2004) 7-factor alphas over the past 12 months (*FH12*). *Q1* to *Q4* refer to the four quartiles of *TSTAKE* for cases where *TSTAKE* exceeds 0%. The baseline is 0% *TSTAKE*. All regressions include fixed effects for fund style and year-month. Control variables, omitted for conciseness, include log fund AUM ( $\log(AUM)$ ), fund age (*FAGE*), management fee (*MFEE*), incentive fee (*IFEE*), high-water mark (*HWM*), lockup (*LOCKUP*), and log restriction period ( $\log(REST)$ ). All variables are either observed at the end of annual intervals or are time-invariant.
- Panel B focuses on hedge funds that transition between team and solo management. Performance is measured as monthly style-adjusted return (*SA*) or monthly Fung-Hsieh 7-factor alphas (*FH*). All regressions in Panel B control for  $\log(AUM)$  at prior month-end, and include fixed effects for fund and year-month.
- Panel C replicates Panel A using Sample #2 instead of Sample #1.

**Panel A: Regressions on fund performance**

Time frame:	Apr. 2007 to Dec. 2023		Dec. 2011 to Dec. 2023 (incl. Form ADV data)			
Dependent variable:	<i>SA12</i> (%)	<i>SA12</i> (%)	<i>SA12</i> (%)	<i>SA12</i> (%)	<i>SA12</i> (%)	<i>FH12</i> (%)
	(1)	(2)	(3)	(4)	(5)	(6)
<i>TEAM</i>	-0.052** (-2.290)		-0.060* (-1.827)	-0.011 (-0.205)	0.039 (0.537)	0.142* (1.842)
<i>TEAMSIZ</i>		-0.037*** (-2.791)				
<i>TEAM</i> × <i>TSTAKE</i>				-0.106 (-1.195)		
<i>TSTAKE</i>			0.190*** (3.408)	0.225*** (3.414)		
<i>TEAM</i> × <i>Q1</i>					-0.069 (-0.716)	-0.100 (-0.992)
<i>TEAM</i> × <i>Q2</i>					-0.164* (-1.756)	-0.241** (-2.249)
<i>TEAM</i> × <i>Q3</i>					-0.136 (-1.163)	-0.162 (-1.370)
<i>TEAM</i> × <i>Q4</i>					-0.122 (-1.134)	-0.213* (-1.805)
<i>Q1</i>					0.154** (2.396)	0.116* (1.679)
<i>Q2</i>					0.165** (2.585)	0.099 (1.443)
<i>Q3</i>					0.253*** (3.335)	0.218*** (2.818)
<i>Q4</i>					0.297*** (3.668)	0.278*** (3.019)
Add. fund controls	Yes	Yes	Yes	Yes	Yes	Yes
FE (style, year)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,732	22,732	6,510	6,510	6,510	6,081
Adj. $R^2$	0.014	0.014	0.014	0.015	0.015	0.067
Within adj. $R^2$	0.014	0.014	0.011	0.011	0.012	0.033

**Panel B: Endogeneity**

Time frame:	Oct. 2004 to Dec. 2023		Dec. 2011 to Dec. 2023 (incl. Form ADV data)				
Dependent variable:	<i>SA</i> (%)	<i>SA</i> (%)	<i>SA</i> (%)	<i>SA</i> (%)	<i>SA</i> (%)	<i>SA</i> (%)	<i>FH</i> (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>TEAM</i>	0.007 (0.113)		0.291* (1.859)			0.447** (2.036)	0.459** (2.277)
<i>TEAMSIZ</i>		-0.016 (-0.423)		0.156* (1.957)			
<i>TEAM</i> × <i>TSTAKE</i>						-0.369 (-0.756)	-0.607 (-1.404)
<i>TSTAKE</i>					0.091 (0.437)	0.069 (0.186)	0.338 (0.846)
Control for lagged AUM	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE (fund, year-month)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,845	49,845	10,480	10,480	10,480	10,480	9,648
Adj. $R^2$	0.010	0.010	0.009	0.008	0.008	0.008	0.062
Within adj. $R^2$	0.003	0.003	0.003	0.003	0.003	0.003	0.001

Panel C: Regressions on fund performance (Sample #2)

Time frame:	Oct. 2004 to Dec. 2023		Dec. 2011 to Dec. 2023 (incl. Form ADV data)			
	<i>SA12</i> (%) (1)	<i>SA12</i> (%) (2)	<i>SA12</i> (%) (3)	<i>SA12</i> (%) (4)	<i>SA12</i> (%) (5)	<i>FH12</i> (%) (6)
<i>TEAM</i>	-0.118* (-1.856)		-0.077 (-1.226)	0.250* (1.756)	0.082 (0.498)	0.375 (1.502)
<i>TEAMSIZ</i>		-0.050 (-1.435)				
<i>TEAM</i> × <i>TSTAKE</i>				-0.480*** (-2.621)		
<i>TSTAKE</i>			0.159 (1.646)	0.314*** (2.707)		
<i>TEAM</i> × <i>Q1</i>					0.153 (0.714)	-0.291 (-0.975)
<i>TEAM</i> × <i>Q2</i>					-0.314 (-1.636)	-0.614* (-1.959)
<i>TEAM</i> × <i>Q3</i>					-0.112 (-0.646)	-0.460* (-1.731)
<i>TEAM</i> × <i>Q4</i>					-0.501** (-2.009)	-0.599** (-2.002)
<i>Q1</i>					-0.107 (-1.014)	0.187 (0.900)
<i>Q2</i>					0.079 (0.670)	0.248 (1.152)
<i>Q3</i>					0.114 (1.120)	0.319 (1.614)
<i>Q4</i>					0.316 (1.494)	0.285 (1.158)
Add. fund controls	Yes	Yes	Yes	Yes	Yes	Yes
FE (style, year)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,212	3,212	1,750	1,750	1,750	1,709
Adj. $R^2$	0.001	0.001	-0.002	0.000	0.000	0.044
Within adj. $R^2$	0.008	0.007	0.009	0.011	0.011	0.006

**Table 2.8:** Effect of *SKIN* and fund domicile on the flow-performance relationship

*Note.* Using Sample #2, the table studies the effects of insider ownership (*SKIN*) and fund domicile on the flow-performance relationship. It reports the results of multivariate regressions on future hedge fund flows. In Panel A, the observation frequency is quarterly. The dependent variable are fund flows over the next quarter (Columns 1 and 2), the next half year (3 and 4), or next year (5 and 6). The regressions control for fund flows over the last quarter (Columns 1 and 2), half year (Columns 3 and 4), or year (Columns 5 and 6), respectively. For example, *FLOW12* ( $t + 4$ ) in Columns 5 and 6 represents fund flows over the last 12 months in 4 quarters' time (i.e., over the next year), and we control for fund flows over the prior year (*FLOW12*). Regressions are estimated separately for US-domiciled ("onshore") and offshore hedge funds. Fund domiciles are taken from EurekaHedge, and, if missing, from Form ADV (Schedule D). The explanatory variable of interest is the interaction term between *RANK\_CA12* and *INSIDER*, where *RANK\_CA12* is the fund's CAPM alpha rank in the prior year, while *INSIDER* is an indicator variable equal to 1 for above-median *SKIN*, and 0 otherwise (Gupta & Sachdeva, 2022).

In Panel B, the observation frequency is monthly, and the dependent variable are fund flows over the next month, *FLOW1* ( $t + 1$ ). Only hedge funds with quarterly (Columns 1 to 4) or monthly (Columns 5 to 6) redemption frequency are considered. *QEND* is a dummy variable equal to one if the month is a calendar quarter-end (March, June, September, or December), and 0 otherwise. *FLOW1* refers to fund flows during the prior month.

In Panels A and B, the additional fund control variables, omitted for conciseness and detailed in the notes accompanying Table 2.2, include log fund AUM ( $\log(AUM)$ ), fund age (*FAGE*), management fee (*MFEE*), incentive fee (*IFEE*), high-water mark (*HWM*), lockup (*LOCKUP*), log restriction period ( $\log(REST)$ ), and subscription frequency (*SUBFREQ*). Panel A includes fixed effects for year-month and style, and Panel B includes fixed effects for year and style. Standard errors are clustered by fund and year-month in Panel A. Panel B uses White's heteroskedasticity-consistent standard errors. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A:** Effect of *SKIN* and fund domicile on net flows

Dependent variable: Fund type:	<i>FLOW3</i> ( $t + 1$ )		<i>FLOW6</i> ( $t + 2$ )		<i>FLOW12</i> ( $t + 4$ )	
	Onshore	Offshore	Onshore	Offshore	Onshore	Offshore
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RANK_CA12</i> × <i>INSIDER</i>	-0.009 (-0.492)	-0.049** (-2.017)	-0.029 (-0.712)	-0.128** (-2.400)	-0.124 (-1.281)	-0.291** (-2.366)
<i>RANK_CA12</i>	0.078*** (4.550)	0.094*** (5.826)	0.154*** (4.242)	0.218*** (5.472)	0.356*** (3.712)	0.474*** (4.662)
<i>FLOW3</i>	0.129*** (4.341)	0.218*** (6.911)				
<i>FLOW6</i>			0.134*** (4.336)	0.193*** (5.943)		
<i>FLOW12</i>					0.064* (1.721)	0.094*** (3.215)
<i>INSIDER</i>	0.011 (1.026)	0.020* (1.873)	0.029 (1.255)	0.054** (2.090)	0.076 (1.538)	0.151** (2.324)
Add. fund controls	Yes	Yes	Yes	Yes	Yes	Yes
FE (fund, YM)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,778	2,181	3,622	2,077	3,283	1,880
Adj. $R^2$	0.079	0.096	0.097	0.122	0.109	0.136
Within adj. $R^2$	0.069	0.090	0.092	0.108	0.108	0.109

**Panel B:** Effect of *SKIN* and fund domicile on inflows versus outflows

	Dependent variable: <i>FLOW1</i> ( $t + 1$ )							
	Quarterly redemption frequency						Monthly red. freq.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>QEND</i>	-0.724*** (-4.817)	-0.825*** (-5.331)	-1.065*** (-6.545)	-1.194*** (-6.972)	-0.928*** (-4.232)	-1.087*** (-4.696)	-0.100 (-0.323)	0.080 (0.244)
<i>INSIDER</i> × <i>QEND</i>	0.502** (2.383)	0.458** (2.053)			0.446** (2.129)	0.404* (1.838)	0.494 (1.518)	0.283 (0.798)
<i>INSIDER</i>	-0.205* (-1.866)	-0.072 (-0.598)			-0.177 (-1.634)	-0.053 (-0.443)	-0.065 (-0.360)	-0.099 (-0.462)
<i>ONSHORE</i> × <i>QEND</i>			0.461** (2.405)	0.499** (2.473)	0.347 (1.492)	0.435* (1.798)	-0.073 (-0.210)	-0.030 (-0.079)
<i>ONSHORE</i>			-0.019 (-0.198)	-0.095 (-0.891)	-0.166 (-1.448)	-0.150 (-1.182)	0.079 (0.431)	-0.207 (-0.936)
<i>RANK_CA12</i>	2.560*** (13.853)	2.394*** (11.961)	3.029*** (20.396)	2.833*** (18.044)	2.561*** (13.860)	2.394*** (11.961)	2.605*** (8.882)	2.815*** (8.943)
<i>FLOW1</i>	-0.010 (-0.801)	-0.023* (-1.756)	0.006 (0.544)	-0.002 (-0.225)	-0.010 (-0.797)	-0.023* (-1.748)	0.016 (0.703)	0.006 (0.233)
Add. fund controls	No	Yes	No	Yes	No	Yes	No	Yes
FE (year, style)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,579	11,269	22,600	20,763	12,579	11,269	6,426	5,652
Adj. $R^2$	0.023	0.032	0.030	0.036	0.023	0.032	0.020	0.023
Within adj. $R^2$	0.020	0.029	0.026	0.032	0.020	0.029	0.013	0.014

**Table 2.9:** *SKIN* during the hedge fund life cycle

*Note.* Using Sample #1, the table studies determinants of monthly levels of *SKIN* (Columns 1 and 2) and of quarterly changes in *SKIN* (Columns 3 to 7). The variables *FAGE\_BEF* and *FAGE\_AFT* represent the piecewise linear components of fund age (*FAGE*) around the previously estimated breakpoint at 6.34 years. *FAGE* is fund age at the end of the month (Columns 1 and 2) or quarter (Columns 3 to 7).  $\log(AUM) (t - 1)$  is the logarithm of AUM at prior quarter-end. *FLOW3* are fund flows and  $\Delta NINV$  is the change in the number of investors during the quarter. *RETQ* ( $t - 1$ ) and *RETQ* are fund returns during the prior and current quarter, respectively. *TEAMSIZE* is the number of portfolio managers at quarter-end; *TSTAKE* is the cumulative equity ownership of these managers. *MFEE* and *IFEE* represent management and incentive fees, respectively. For presentation purposes, all variables are expressed in percentages except *FAGE*,  $\log(AUM)$ ,  $\Delta NINV$ , and *TEAMSIZE*. Standard errors are clustered by fund and year-month. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Observ. freq.: Depend. variable:	Monthly <i>SKIN</i> (%)		Quarterly $\Delta SKIN\_QLY$ (%)				
	(1)	(2)	(3)	(4)	(5)	<i>FAGE</i> < 6.34 yrs (6)	<i>FAGE</i> ≥ 6.34 yrs (7)
<i>AGE_BEF</i>	-1.390*** (-2.956)						
<i>AGE_AFT</i>	1.017*** (6.317)						
<i>FAGE</i>		-0.451 (-1.307)			0.023*** (3.712)	0.111 (1.102)	0.008 (1.193)
<i>FAGE</i> squared		0.043*** (3.732)					
$\log(AUM) (t - 1)$			-0.825*** (-4.494)	-0.834*** (-4.039)	-0.089*** (-2.697)	-0.239** (-2.079)	-0.066*** (-2.879)
<i>FLOW3</i> (%)			-0.013*** (-3.864)	-0.012*** (-3.388)	-0.015*** (-5.049)	-0.010** (-2.068)	-0.016*** (-4.602)
$\Delta NINV$			-0.027*** (-4.272)	-0.029*** (-3.925)	-0.033*** (-4.819)	-0.070*** (-3.531)	-0.030*** (-3.756)
<i>SKIN</i> ( $t - 1$ ) (%)			-0.086*** (-5.841)	-0.087*** (-5.796)	-0.009*** (-3.792)	-0.028*** (-4.093)	-0.001 (-0.512)
<i>RETQ</i> ( $t - 1$ ) (%)			0.007** (2.600)	0.007** (2.121)	0.002 (0.461)	-0.003 (-0.160)	0.002 (0.691)
<i>RETQ</i> (%)			0.000 (0.034)	0.000 (-0.026)	0.001 (0.263)	0.003 (0.259)	0.000 (0.036)
<i>TEAMSIZE</i>				-0.071 (-0.556)	0.029 (0.676)	-0.035 (-0.345)	0.052 (1.207)
<i>TSTAKE</i> (%)				-0.215 (-0.359)	-0.050 (-0.418)	-0.088 (-0.243)	-0.093 (-0.888)
<i>MFEE</i> (%)					0.228** (2.463)	-0.272 (-0.886)	0.282*** (3.156)
<i>IFEE</i> (%)					0.019** (2.485)	0.057** (2.005)	0.007 (1.335)
FE fund	Yes	Yes	Yes	Yes	No	No	No
FE year-quarter	No	No	Yes	Yes	Yes	Yes	Yes
Observations	73,230	73,230	19,557	16,519	16,489	3,450	13,039
Adj. $R^2$	0.827	0.826	0.116	0.124	0.026	0.026	0.029
Within adj. $R^2$	0.037	0.032	0.062	0.065	0.024	0.035	0.024

## 2.A Appendix

### 2.A.1 Excerpts from the Form ADV glossary

The following definitions are drawn from the Form ADV glossary, as published by the SEC.<sup>48</sup> In this Chapter 2, the variable *CONTROL* is set to 1 if the hedge fund manager exercises “Control”. The variable *SKIN* represents the percentage of the hedge fund owned by all “Related Persons”.

“1. **Advisory Affiliate:** Your advisory affiliates are (1) all of your officers, partners, or directors (or any *person* performing similar functions); (2) all *persons* directly or indirectly controlling or *controlled* by you; and (3) all of your current *employees* (other than *employees* performing only clerical, administrative, support or similar functions). [...]

7. **Control:** The power, directly or indirectly, to direct the management or policies of a *person*, whether through ownership of securities, by contract, or otherwise.

- Each of your firm’s officers, partners, or directors exercising executive responsibility (or *persons* having similar status or functions) is presumed to control your firm.
- A *person* is presumed to control a corporation if the *person*: (i) directly or indirectly has the right to vote 25 percent or more of a class of the corporation’s voting securities; or (ii) has the power to sell or direct the sale of 25 percent or more of a class of the corporation’s voting securities.
- A *person* is presumed to control a partnership if the *person* has the right to receive upon dissolution, or has contributed, 25 percent or more of the capital of the partnership.
- A *person* is presumed to control a limited liability company (‘LLC’) if the *person*: (i) directly or indirectly has the right to vote 25 percent or more of a class of the interests of the LLC; (ii) has the right to receive upon dissolution, or has contributed, 25 percent or more of the capital of the LLC; or (iii) is an elected manager of the LLC.
- A *person* is presumed to control a trust if the *person* is a trustee or *managing agent* of the trust. [...]

27. **Managing Agent:** A *managing agent* of an investment adviser is any *person*, including a trustee, who directs or manages (or who participates in directing or managing) the affairs of any unincorporated organization or association that is not a partnership. [...]

34. **Person:** A natural person (an individual) or a company. A company includes any partnership, corporation, trust, limited liability company (‘LLC’), limited liability partnership (‘LLP’), sole proprietorship, or other organization. [...]

38. **Related Person:** Any *advisory affiliate* and any *person* that is under common *control* with your firm. [...]

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<sup>48</sup>The Form ADV glossary is available at <https://www.sec.gov/files/rules/final/2011/ia-3221-appc.pdf>.



## Chapter 3

# The (In)visible Women in the Hedge Fund Industry

### 3.1 Introduction

Despite the importance of hedge funds in financial markets, the choice process of hedge fund investors remains unclear. Based on previous work on mutual funds, some studies have successfully identified various factors that drive hedge fund flows, in particular the past performance of the fund (Agarwal et al., 2004; Agarwal et al., 2018; Fung et al., 2008; Lim et al., 2016). The strategic motivations of hedge fund firms to launch funds also resemble those of mutual fund firms (Fung et al., 2021; Kolokolova, 2011). However, the distribution process of hedge funds is very different from that of mutual funds: mutual funds, as retail products, are typically distributed without personal interaction between fund representatives and investors, whereas hedge fund distribution often involves such direct interactions. In this chapter, we analyze whether and how these interactions affect hedge fund flows.

Investor contact persons play an important role in the distribution of hedge funds. Unlike mutual funds, which are primarily held by households, investments in hedge funds are primarily made by investment professionals (“allocators”) on behalf of institutions representing pensioners, endowment donors, or taxpayers. These allocators are formally required to conduct extensive due diligence before approving an investment. Such due diligence processes involve the exchange of objective information, contained in subscription documents, due diligence questionnaires, or customized portfolio evaluations (Travers, 2012). However, in a dialogue that typically spans months,<sup>1</sup> personal interactions between representatives of the hedge fund and its potential investors often extend beyond formal meetings to include “schmoozing” (Lakonishok et al., 1992, p. 375) gatherings, such as dinners or cocktail events. For example, hedge funds donate to charities in order to network with potential investors at fundraising galas (Agarwal et al., 2021).

Personal relationships thus become important and so does the role of investor contact persons; their ability to establish trust – not only based on past performance but through communication, persuasion, and familiarity – can significantly influence investment decisions, potentially to the detriment of end

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<sup>1</sup>Anecdotally, one marketer at a hedge fund states that it requires “30+ hours of my time to work with an investor from initial contact to investment allocation, when you include all the questions via email, conference calls, face-to-face meetings, etc.” as cited in the Bloomberg/AIMA “Hedge Fund Start-Up Guide”. The publication is available at <https://www.bloomberg.com/professional/insights/markets/hedge-fund-start-up-guide/>.

investors (Gennaioli et al., 2015; Goyal et al., 2023). We argue that the extensive personal contact between contact person (CP) and investor exposes the investor to emotional biases stemming from personal attributes of the CP. In evaluating the fund, the investor must assess intangible qualities such as the character, trustworthiness, and experience of the hedge fund staff – judgments that are inherently subjective. Although the CP may not be the intended object of evaluation, engaging in this type of subjective assessment can unconsciously prime the investor to be more receptive to other subjective influences (Bargh et al., 1996). The hedge fund literature has largely overlooked the investor solicitation process, focusing instead on investors’ reactions to historical fund characteristics and portfolio manager traits, while implicitly treating the investor’s choice process as immediate.

Unlike mutual funds, which incur significant advertising expenses (Roussanov et al., 2021), hedge funds predominantly use listings in commercial hedge fund databases, such as TASS, to reach potential investors (Jorion & Schwarz, 2014). These databases provide the CPs’ contact details – email, fax, phone, website, and office address – enabling subscribing investors to initiate contact. Our empirical study leverages 180 historical snapshots of the TASS database from 2007 to 2024. Using these historical snapshots is important because the TASS database contains only current information on a fund’s personnel. By combining these snapshots, we can infer the tenures of CPs and portfolio managers (PMs). The potentially high career mobility of CPs<sup>2</sup> renders these tenures a critical element of our analysis and may explain the scarcity of prior empirical work in this area.

Our study yields a simple conclusion: hedge fund investors prefer female CPs. Specifically, hedge funds with female CPs experience annual flows that are, on average, 2.0% higher than those with male CPs. These results hold after controlling for various fund-specific variables that may influence hedge fund flows, such as the gender of the portfolio manager (Aggarwal & Boyson, 2016); fund performance, fees, and redemption terms (Agarwal et al., 2004); fund size and strategy (Getmansky, 2012); and fund domicile (Aragon et al., 2014). The results are also robust to the inclusion of time-fixed effects, with which we control for the aggregate effect of economy-wide factors, such as changes in regulation (e.g., Bowe et al., 2022). To address endogeneity concerns stemming from unobserved time-invariant differences across funds, we conduct an event study around changes in CP gender. In a difference-in-differences framework, we find that replacing a male CP with a female CP yields better subsequent flows than vice versa.

We then test four potential reasons why hedge funds with female CPs might enjoy better flows. First, female CPs more often hold job titles that indicate an exclusive focus on client acquisition and retention, such as “Investor Relations” or “Business Development”. We refer to such dedicated marketers as “marketing persons” (MPs). While women make up 32% of all CPs, they represent 46% of all MPs. MPs may have stronger marketing skills than CPs whose responsibilities extend beyond marketing, such as fund operations or firm finances. Still, we find that the result is robust to controlling for the higher percentage of MPs among women. In fact, the difference in success between men and women is even more pronounced when we focus on MPs: employing a female MP yields 5.1 percentage points better annual flows than employing a male MP. Similarly, the portfolio manager serves as the CP for 9% of our observations. Fund managers may be poor marketers and, since they are almost exclusively male, may reduce the average flows to funds with male CPs. After excluding CPs who are simultaneously portfolio managers (PMs), we find that female CPs continue to engender better flows.

Second, women may be better at predicting certain fund features that make the fund more attractive

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<sup>2</sup>For example, in a loosely related study, Shi et al. (2017, Footnote 1) cite data from the US Bureau of Labor Statistics according to which the annual turnover rate among business-to-business sales representatives in 2013 was 22%.

for investors. Contrary to this hypothesis, we find no evidence that funds with female CPs have better subsequent performance or that the fund strategies chosen by hedge funds with female CPs generally see more demand.

Third, women may be able to focus their careers on employers with more attractive hedge funds, possibly due to preferential hiring practices or their own strategic career choices. To test this “career mobility” hypothesis, we examine determinants of CP turnover using a multinomial logistic regression framework. We find evidence that women are indeed able to manage their careers more effectively. Specifically, better fund performance makes it more likely that a male CP departs and is replaced by a female CP.

Fourth, flows into hedge funds with female CPs may be influenced by a tendency of male investors to be attracted to the opposite gender (the “attraction story”). In other words, since hedge fund investors are predominantly male, they may gravitate toward female CPs due to emotional appeal or direct attraction. For example, male investors might be more inclined to accept calls or meeting invitations from female CPs, granting the latter better opportunities to build trust and pitch their offerings.<sup>3</sup> We investigate this possibility using data on funds of hedge funds (FoHFs) because the gender of the FoHF manager is observable. We argue that FoHF allocations into hedge funds are substantial enough to affect hedge fund flows in an economically significant manner. Supporting the “attraction story”, we find that flows into hedge funds with female CPs respond more strongly to flows from male-managed FoHFs than from female-managed FoHFs.

This paper contributes to the literature by identifying CP gender as a determinant of hedge fund flows. Given no evidence of a correlation between CP gender and managerial ability, this result raises questions about the objectivity of professional investors. The related hedge fund literature has focused on investors’ suboptimal interpretation of fund characteristics. In particular, hedge fund investors chase past fund performance at both the individual fund level (e.g., Dichev and Yu, 2011; Lim et al., 2016) and the firm level (Fung et al., 2021), while insufficiently controlling for risk-factor exposures when assessing fund performance (Agarwal et al., 2018). The literature on non-financial hedge fund flow determinants has found that diverse fund management teams (Lu et al., 2024), as well as fund managers who are perceived as more trustworthy (Pareek & Zuckerman, 2014), or who resemble the investor in terms of gender (Aggarwal & Boyson, 2016) or ethnicity (Lu et al., 2022), tend to attract better flows.<sup>4</sup> In a recent paper, Joenväärä and Tiu (2023) find that some investors prefer hedge funds with salient or compelling names, even though these hedge funds subsequently underperform. We add to this literature by proposing the gender of the fund’s contact person as an additional variable explaining investor behavior.

The remainder of this chapter is organized as follows: Sections 3.2 and 3.3 explain our data collection process and describe our sample, respectively. Empirical results are presented in Sections 3.4 and 3.5. Section 3.4 establishes that female CPs generate better flows, and Section 3.5 discusses possible reasons for this phenomenon. Section 3.6 concludes, and Appendix 3.A.2 details how our main results can be replicated.

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<sup>3</sup>In a related study of consumer credit demand in South Africa, Bertrand et al. (2010) find that including a photo of an attractive woman in direct mail solicitations increases loan demand by the equivalent of a 25% reduction in the interest rate.

<sup>4</sup>Such “homophily” has also been observed for mutual fund managers and investors (e.g., Kumar et al., 2015; Niessen-Ruenzi and Ruenzi, 2019).

## 3.2 Data

### 3.2.1 Sample construction

The data used in this chapter stem from different versions of the Lipper Hedge Fund Database (“TASS”). TASS has been widely used in the academic literature on hedge funds. In a recent, March 2024 version, TASS contains information on 18,887 hedge funds. Although TASS generally includes liquidated (“dead”) funds, we find that a number of funds have nonetheless been removed from the database. To ensure our dataset’s comprehensiveness, we combine the March 2024 TASS version with earlier versions to recover hedge funds that have been removed. This combination increases the number of hedge funds to 21,618. Following prior work, we next restrict the sample to funds that report USD-denominated net (instead of gross) returns at monthly (instead of only quarterly) frequency. Applying these filters shrinks the sample from 21,618 to 11,212 hedge funds.

We then merge the sample with 180 historical TASS snapshots between April 2007 and January 2024. We include data from May 2005 onwards, allowing us to start estimating factor loadings in the 24 months before the snapshots begin. Some funds are represented in TASS with different share classes. In an exercise of customer segmentation, these share classes typically target different investor groups by modulating fees, minimum investment amounts, or lockup periods.<sup>5</sup> We retain duplicate share classes in this chapter. Our final sample, including the restrictions detailed below, comprises 6,301 hedge funds. It includes both single hedge funds (4,519) and funds of hedge funds (1,782).

### 3.2.2 Determining employee tenure, gender, age, and job role

For each fund, TASS provides information on two types of employees: portfolio managers (PMs) and contact persons (CPs). As discussed in Section 2.4.1, TASS includes historical data only on fund returns and assets under management (AUM). All qualitative data, including information on PMs and CPs, is static, with only the most recent entries being reported. The historical snapshots enable us to reconstruct the employment histories of CPs and PMs; turnover events can be inferred by comparing consecutive snapshots. However, a change in CP or PM may be reported with a delay, or the change in the respective data field may result from an error correction rather than a real event (see Section 2.4.1). Still, these issues are likely less severe for changes in CPs for two reasons. First, fund firms and CPs have incentives to report CP changes promptly. Both parties want prospective investors not only to reach the current CP but also not to reach the former CP (who may have joined a competitor). In terms of data quality, determining whether a change merely reflects an error correction is easier for the CP field (e.g., “James” instead of “Jams”) than for quantitative fields (e.g., 5% vs. 15% performance fee). Second, to the extent that the database itself is the solicitation channel (Jorion & Schwarz, 2014), the change in the database, rather than the actual CP replacement, is the relevant event, rendering any potential reporting delay irrelevant. For example, investors may be more inclined to call a phone number in a database if there is a female name attached to it.

Table 2.1 reports the availability of the TASS snapshots. The mostly monthly frequency of the

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<sup>5</sup>A common issue is that AUM and fund returns are typically reported at the fund level rather than at the share-class level. Researchers usually choose to analyze only the share class with the longest track record, which is often an “early bird” or “founder” class. These classes tend to be the most investor-friendly in terms of both fees and fund liquidity. However, as fund AUM increases, the terms of these early classes may no longer accurately reflect the terms faced by the investors.

snapshots aligns with the monthly frequency of the return and AUM data in TASS. As in Chapter 2, we do not rely on potentially biased information that hedge fund employees have retroactively decided to make public (such as *LinkedIn* biographies). Although our analysis is limited to TASS, it can be reasonably assumed that the CP listed in TASS is also the primary liaison for investors who contact the fund through other channels.

To determine the gender of each CP and PM, we use the prefixes (such as “Mr.” and “Mrs.”) reported to TASS, which are available for 66% of individuals. For the remaining individuals, we follow Lu et al. (2022) in applying the *genderize.io* API to their first names (33%), and assign gender manually in case the API fails (0.4%). The age of each individual is determined based on first names and locations using the *agify.io* API, which sources data from public submissions of first names and ages. We exclude observations from funds that either leave the CP field blank or input an entity (e.g., “Marketing Team” or “Fund XYZ Investor Relations”) instead of a natural person.

We use the job titles provided by TASS to clarify the roles of each CP, as detailed in Table 3.2 and Appendix 3.A.1. While TASS categorizes every CP under the label “Marketing”, their job titles reveal that not all CPs are actually marketers. Instead, titles such as “CFO”, “COO”, and “Portfolio Manager” are among the most common. Conversely, such titles as “Business Development”, “Director of Marketing”, and “Investor Relations” indicate that the CP’s primary responsibility is indeed marketing. We selected TASS because it provides these job titles, which we utilise to segregate CPs into dedicated “marketing persons” (MPs) and those with roles outside of marketing (non-MPs).<sup>6</sup> Among a total of 5,032 CPs, we identify 837 MPs and 566 non-MPs, leaving 3,629 CPs unclassified. We assign 501 of these unclassified CPs to the non-MP category because they are simultaneously listed as PMs.<sup>7</sup> Figure 3.1 illustrates the gender distribution across the subgroups of CPs and PMs. While females constitute 32% of all CPs, they are overrepresented among MPs (46%) and underrepresented among non-MPs (21%). We therefore control for the relatively higher percentage of MPs among female CPs when later comparing the asset-raising success of male and female CPs.

Finally, although our primary focus is on CP categorization, it is noteworthy that not every individual labeled as “Portfolio Manager” is genuinely a fund manager. Female PMs, in particular, frequently hold titles that contradict a portfolio-management role, the most common being “Client Service” and “Marketing”. The job titles suggest that 24% (!) of female PMs may be mislabeled, an arguably overlooked phenomenon in existing research on female hedge fund PMs. The mislabeling obscures the true representation of women, who comprise 6.4% of all PMs but a mere 4.9% of those correctly labeled

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<sup>6</sup>CPs may be MPs even if their job titles suggest otherwise. For example, a marketer may be given a nominal “portfolio manager” title because investors might be more interested in speaking with a “portfolio manager” than a “marketing associate”. Still, the goal of our classification is not to definitively identify marketers, but to facilitate a fair comparison between male and female CPs. Nominal titles could only be problematic for our conclusions if they were more often given to female CPs. Our data suggest otherwise. Table 3.2 shows the gender distribution among the most popular job titles within each CP and PM classification group. Women less often hold titles that suggest seniority, such as “Director of Marketing”, and are more frequently recorded in the database without any title (see the “(None or missing)” category for *both* CPs and PMs). The fact that women are less often assigned senior titles weakly suggests that they are also less likely to receive nominal titles. In line with the assumption that hedge fund firms have no incentive to inflate the role of female CPs, Kricheli-Katz (2019) finds that male managers in high-status occupations can experience “identity threat” when women enter their domain, leading to poorer evaluations and lower pay for these women. Similarly, women in leadership roles face prejudice as their role is perceived as conflicting with the female gender role (“role incongruity” theory, Eagly and Karau, 2002). Notably, gender-based biases against women in leadership are not exclusive to men; for example, in the Grossman et al. (2019, p. 4) study, such biases were held “primarily by female followers”.

<sup>7</sup>This rule is not applied if the PM is mislabeled, that is, if the PM’s job title contradicts a portfolio-management role.

as PMs (see Table 3.2). As funds with female PMs are often funds of hedge funds (FoHFs) (Aggarwal & Boyson, 2016), excluding FoHFs lowers the representation further, to 4.2%. These figures fall below the approximate 10% of women among mutual fund managers (Niessen-Ruenzi & Ruenzi, 2019).

### 3.2.3 Hedge fund returns and AUM

We correct obvious errors in returns and AUM upon identification.<sup>8</sup> We complement our data with the UNION dataset, which combines five major commercial hedge fund databases: BarclayHedge, EurekaHedge, HFR, Morningstar, and TASS.<sup>9</sup> Nonetheless, we have to omit a large number of funds (20%) that do not report any AUM data to any of these databases. For non-missing AUM observations, we set a lower limit of USD 1 million to avoid excessively low logarithmic values.

We address a potential “instant history” bias (Fung & Hsieh, 2000) by removing backfilled returns in three steps. First, we obtain the database addition dates from TASS and a recent version of EurekaHedge to identify and exclude any returns preceding a fund’s inclusion in either database.<sup>10</sup> Second, for the 8% of funds lacking addition dates, we infer these dates from the time of the fund’s first appearance in our historical TASS snapshots, a method employed by Jorion and Schwarz (2019). Figure 3.2 illustrates the relationship between the TASS-reported database addition dates and the dates of first appearance in our snapshot sample. The earliest possible first appearance is April 2007, by construction. After April 2007, the addition dates closely track the first-appearance dates, justifying our method to infer addition dates from first-appearance dates. Third, for the small fraction (0.1%) of funds with missing addition dates and database entrance on or before April 2007, we exclude the first 12 months of observations after launch (as in Bali and Weigert, 2024). However, observations from April 2007 onward are retained, as any backfilled observations during this period were removed in the first two steps.

### 3.2.4 Variable construction

**Investment styles** Following Agarwal et al. (2009), we categorize the twelve TASS fund strategies into four investment styles (“Directional Traders”, “Relative Value”, “Security Selection”, and “Multiprocess”). We add two further styles, “FoHF” and “Other”, for FoHFs and funds of unspecified strategy, respectively.

**AUM flows** We approximate fund flows as the change in AUM, adjusted for fund return (Sirri & Tufano, 1998). For flows over the prior 12 months:

$$FLOW12_{i,t} = \frac{AUM_{i,t}}{AUM_{i,t-12}} - \prod_{j=0}^{11} (1 + RET_{i,t-j}), \quad (3.1)$$

where  $AUM_{i,t}$  is the AUM of fund  $i$  at the end of month  $t$ , and  $RET_{i,t}$  is its net (after-fee) return during

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<sup>8</sup>For example, even after restricting to monthly reporting funds, TASS often calculates returns using Net Asset Values (NAVs) that are more than one month apart due to missing observations. We remove these returns.

<sup>9</sup>As mentioned in Chapters 1 and 2, Agarwal et al. (2017) provide details on a previous version of the UNION dataset. The dataset has since been updated to include data through December 2022, and the BarclayHedge database has been added.

<sup>10</sup>Removing pre-entry-date data to avoid backfill bias is recommended by Malkiel and Saha (2005) and Posthuma and van der Sluis (2003). While this approach is effective, it is also “very costly in terms of informational content” (Fung & Hsieh, 2009, p. 37). To reduce this cost, we use the earlier of the two addition dates from TASS or EurekaHedge for funds that report to both databases. Notably, this approach could reintroduce the bias if we relied solely on TASS for returns data (because the returns would either be backfilled or missing in TASS). However, since we also incorporate data from the UNION dataset, which includes EurekaHedge, returns that were chosen not to be backfilled into TASS are nonetheless included.

month  $t$ . To mitigate the effect of outliers, we require at least USD 5 million in AUM to calculate flows and apply winsorization at the 1st and 99th percentiles to the flow data.

**Performance measures** We use CAPM alpha to measure fund performance, because Agarwal et al. (2018) demonstrate that hedge fund flows are better explained by CAPM alpha than by either raw fund returns or alphas derived from more sophisticated models. As in Chapter 2 and Agarwal et al. (2018), we estimate a CAPM beta using monthly data over 24-month rolling intervals, and then calculate the CAPM alpha for the final 12 months of each interval. Specifically, we fit the following regression for months  $t - 23$  to  $t$  to retrieve the factor loadings at time  $t$ :

$$RET_{i,t} - RF_t = a_i + \beta_i RMRF_t + \varepsilon_{i,t}, \quad (3.2)$$

where  $RET_{i,t} - RF_t$  is fund  $i$ 's net excess return over the risk-free rate in month  $t$ . The realizations of the market factor,  $RMRF$ , and the proxy for the risk-free rate,  $RF$ , are obtained from Kenneth French's website. As in Chapter 2, we include the residuals when calculating alphas. We then calculate the average of these monthly alphas over the prior 12 months ( $CA12$ ):

$$CA12_{i,t} = \frac{\sum_{s=t-11}^t \alpha_{i,s}}{12} = \frac{\sum_{s=t-11}^t (a_i + \varepsilon_{i,s})}{12}. \quad (3.3)$$

Finally, for each fund and month, we calculate the relative rank in terms of  $CA12$  ( $RANK\_CA12$ ):

$$RANK\_CA12_{i,t} = \frac{\text{rank}(CA12_{i,t})}{N_t + 1}, \quad (3.4)$$

where  $N$  denotes the total number of funds in month  $t$  with non-missing  $CA12$ . In robustness tests, we also consider cumulative net returns ( $RET12$  and  $RANK\_RET12$ ) and average Fung and Hsieh (2004) 7-factor alphas ( $FH12$  and  $RANK\_FH12$ ), each over 12-month periods.

### 3.3 Descriptive statistics

Panel A of Table 3.3 summarizes our hedge fund sample, which includes data for 6,301 USD-denominated hedge funds and FoHFs from May 2005 to December 2023. The average fund achieves a cumulative annual net return of 2.94% ( $RET12$ ) and an average monthly CAPM alpha (over rolling 12-month periods) of  $-0.06\%$  ( $CA12$ ). It has USD 210 million of AUM ( $AUM$ ), and 6.4 years of return history ( $FAGE$ ). Median management and performance fees are 1.5% and 20% per annum ( $MFEE$  and  $IFEE$ ), respectively, which is consistent with industry standards (e.g., Agarwal et al., 2018). The distribution of annual flows ( $FLOW12$ ) is positively skewed. The majority, 54%, of funds employ leverage ( $LEVERED$ ), and 72% subject performance-fee calculation to a high-water-mark provision ( $HWM$ ). 24% of funds are personally invested by their managers ( $PCAP$ ), and 32% are domiciled "onshore", in the US ( $ONSHORE$ ). After an initial lockup period of 3.7 months ( $LOCKUP$ ), the average fund can be redeemed every 69 days ( $REDFREQ$ ) with 43 days prior notice ( $REDNOTI$ ).

Panel B of Table 3.3 reports the number of funds by employee structure and year-end. Our TASS snapshots allow for up to two CPs and up to five PMs to be entered.<sup>11</sup> Throughout the sample period,

<sup>11</sup>The historical TASS files we obtain for our study were intended to be used with *PerTrac*, a hedge fund data and analysis software. We note that TASS files in other formats (*Microsoft Access*, *Microsoft Excel*, and ASCII) allow for up to five CPs and up to eight PMs. We expect the impact to be immaterial given that 86% of observations pertain to funds with one CP and fewer than five PMs.

a single CP and a single PM are most common. The total number of active funds reporting to TASS decreases significantly during our sample period: between 2007 and 2023, the number shrinks by 88%, from 2,521 to 312. We include time fixed effects in our later analyses to control for potential time-dependent reporting biases.

Panel C of Table 3.3 categorizes funds by CP gender: female, male, and mixed (both female and male CPs). Notably, funds with female CPs receive better flows on average than those with male CPs, despite their larger size and worse performance. These correlations, while silent on causation, are intriguing given the well-documented, positive flow-performance relationship. Funds with mixed-gender CPs display a conventional combination of lower flows, higher AUM, and older fund age (Getmansky, 2012). These differences underscore the need to include control variables in the regression analysis in Section 3.4, which investigates the impact of CP gender on fund flows.

### 3.4 Male versus female contact persons

#### 3.4.1 Flows into hedge funds with male versus female contact persons

Do investors prefer hedge funds with female contact persons (CPs)? To investigate, we explore determinants of fund flows using a multivariate regression setup. We control for alternative determinants of fund flows to verify that the results are not driven by observable differences between female- and male-CP funds:

$$\begin{aligned}
 FLOW12_{i,t+12} = & a + \beta_1 FEMALE\_CP_{i,t} + \beta_2 FEMALE\_PM_{i,t} + \beta_3 RANK\_CA12_{i,t} \\
 & + \beta_4 \log(AUM_{i,t}) + \beta_5 BROKER_i + \beta_6 MFEE_i \\
 & + \beta_7 IFEE_i + \beta_8 HWM_i + \beta_9 LOCKUP_i \\
 & + \beta_{10} LEVERED_i + \beta_{11} FAGE_{i,t} + \beta_{12} \log(REST_i) \\
 & + \beta_{13} \log(MININV_i) + \beta_{14} PCAP_i + \beta_{15} ONSHORE_i \\
 & + \sum_k \beta_{16}^k YM\_FE_t^k + \sum_l \beta_{17}^l STYLE\_FE_i^l,
 \end{aligned} \tag{3.5}$$

where  $FLOW12_{i,t+12}$  are the flows of fund  $i$  in the 12-month period up to month  $t + 12$  (i.e., from month-end  $t$  to month-end  $t + 12$ ). We observe all variables at 12-month intervals to avoid autocorrelation in the dependent variable.  $FEMALE\_CP$  is an indicator variable equal to 1 if fund  $i$ 's CPs at month-end  $t$  are all female, and 0 if they are all male. In our main analysis, we omit observations of funds with both male and female CPs.  $FEMALE\_PM$  indicates whether all PMs are female.  $RANK\_CA12$  is the fund's CAPM alpha rank based on the 12-month period up to month  $t$ . In alternative specifications, we measure performance as Fung and Hsieh (2004) 7-factor alpha rank ( $RANK\_FH12$ ) and net-return rank ( $RANK\_RET12$ ).  $AUM$  are fund AUM at the end of month  $t$ , in USD million.  $BROKER$  is a dummy variable indicating whether the fund employs a blue-chip prime broker.<sup>12</sup> Prime brokers may support the fund's asset-raising efforts through the provision of "capital introduction" services.  $MFEE$  and  $IFEE$  are the annual management and performance fees charged by the fund, respectively.  $HWM$  indicates whether the performance fee is subject to a high-water-mark provision.  $LOCKUP$  is the minimum initial duration of investment, in years.  $LEVERED$  indicates whether the fund employs leverage.  $FAGE$  is fund age since inception, in years.  $REST$ , the restriction period, is the sum of redemption frequency and

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<sup>12</sup>Bank of America, Bear Stearns, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan, Merrill Lynch, Morgan Stanley, or UBS.

redemption notice period, each measured in days (Agarwal et al., 2024; Aggarwal & Boyson, 2016). To illustrate, a fund that can be redeemed at quarterly frequency with 60 days' prior notice would have a restriction period of  $90 + 60 = 150$  days. *MININV* is the minimum initial investment amount, in USD. *PCAP* indicates whether the manager has personal capital invested in the fund. *ONSHORE* indicates whether a fund is domiciled in the US.<sup>13</sup> Finally, *YM\_FE* and *STYLE\_FE* are dummy variables for each year-month and fund style, respectively. Standard errors are clustered by fund and year-month to account for potential within-group correlations.

The regression results in Table 3.4 suggest that female CPs benefit fund growth. In Column (1), funds employing a female CP outgrow those with male CPs by an economically relevant 2.0% per annum ( $t = 2.00$ ). The results are robust when we include additional control variables in Column (2) and use different performance measures in Columns (3) and (4). Since we control for PM gender, the effect is unlikely due to investor preferences for “diversity”. We argue that investors prioritizing such values would more likely gravitate towards funds with female PMs than to those with female CPs. To ensure that the results are not skewed by extreme percentage flows into small funds, we repeat the analysis on the subset of observations with at least USD 25 million in AUM (Columns 5 and 6). The economic effect is virtually identical for funds below and above that threshold. Analyzing negative and positive net flows separately in Columns (7) and (8), we observe that the effect is limited to positive net flows. This indicates that female CPs are more effective at generating inflows than at preventing outflows. In Column (9), we exclude FoHFs as they may be considered a distinct category of funds. In Column (10), we use the percentage of female CPs (*FEMALE\_CP\_PERC*) as our explanatory variable. This allows for the inclusion of funds with mixed-gender CP teams, thereby increasing the sample size. The results remain virtually unchanged. Taken together, our findings suggest that female CPs improve flows relative to their male counterparts.

### 3.4.2 Endogeneity

The better flows to hedge funds with female CPs may be driven by unobserved time-invariant differences between hedge funds with female and male CPs. To address this concern, we conduct an event study of changes in flows around CP turnover events. Specifically, we compare funds that increase the percentage of females among their CPs (group 1), reduce this percentage (group 2), or experience a CP-turnover event that does not involve a change in the percentage of CPs that are female (group 3). For example, a fund that replaces a male with a female CP would belong to the first group. To be included in this event study, a fund must have flow data available in both of the 12-month periods before and after the CP change. Excluding funds with insufficient data leaves 605 funds for the event study. Out of these 605 funds analyzed, 158 increase the percentage of female CP (group 1), while 134 do the opposite (group 2). The remaining 313 funds, which underwent a form of CP turnover without a change in the percentage, serve as a plausibility check. We then employ a difference-in-difference analysis to compare changes in fund flows across the three groups.

The results reported in Table 3.5 reveal that hedge funds benefit from increasing the percentage of female CPs. Funds that do so experience a 20.2 percentage point lower decrease in annual net flows compared to funds that replace a female with a male CP. This difference-in-differences estimate is

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<sup>13</sup>Cumming and Dai (2009) document that offshore-domiciled hedge funds attract better flows due to tax benefits over US-domiciled (“onshore”) hedge funds. Aragon et al. (2014) find that offshore hedge funds exhibit a stronger flow-performance relationship than their onshore counterparts, a finding the authors attribute to the stricter marketing restrictions faced by the latter (as discussed in Section 2.6).

economically relevant and statistically significant at the 5% level. It is worth noting that all groups experience a significant reduction in annual flows between the “before” and “after” periods, and flows are consistently positive in the “before” period and negative afterwards. We attribute these general patterns to survivorship bias, as funds with poor flows in the “before” period may be more likely to be closed and thus excluded from the sample. The remainder of Panel A in Table 3.5 confirms that the results are robust to changes in event-window length to 24 and 36 months, respectively. Panel B of Table 3.5 presents a robustness test for which flows are estimated at semi-annual intervals instead of annual intervals. The results are similar to those in Panel A, yet statistically insignificant. In additional robustness tests (not reported here), we repeat the analysis to compare: (1) funds that replace a male CP with a female CP versus those that replace a female CP with a male CP; and (2) funds transitioning from all-male CPs to all-female CPs versus those transitioning in the opposite direction. The results are qualitatively similar. However, the validity of these findings is limited for two reasons. First, contrary to our hypothesis, group (3) – and not group (1) – experiences the least severe reduction in flows. Second, CP turnover events may be endogenous; we analyze their causes in Section 3.5.3. Overall, the findings weakly suggest that the better flows for female-CP funds compared to male-CP funds are not due to unobserved time-invariant differences between the two fund groups.

## 3.5 Underlying causes

What causes the better success of female contact persons (CPs)? We explore four potential explanations. First, female CPs are more often dedicated marketing persons (MPs) and less often portfolio managers (PMs) than male CPs, which may allow them to perform better (“job story”). Second, female CPs might be more skillful in identifying auspicious funds, thus enabling them to associate with the *ex post* better-selling funds (“due diligence story”). Third, female CPs might be able to work with the *ex ante* more attractive hedge funds (“career mobility story”). Lastly, given that investors are predominantly male, we investigate whether investors gravitate towards female-CP funds for non-economic reasons (“attraction story”).

### 3.5.1 Job story

In comparison to their male counterparts, female CPs more often hold job titles that suggest a focus on client acquisition and retention, such as “Investor Relations” or “Business Development” (see Section 3.2.2). We refer to such CPs as “marketing persons” (MPs). MPs may be more specialized and less distracted, thus potentially better at winning investors than CPs with other responsibilities, such as fund operations or firm finances. To investigate whether the success of female CPs is attributable to their higher likelihood of being MPs, we include two dummy variables in Equation 3.5 – *FEMALE\_MP* and *MALE\_MP* – to indicate whether the fund employs a female or male MP, respectively. The results, reported in Columns (1) and (2) of Table 3.6, provide evidence that female MPs positively impact fund flows, while, remarkably, male MPs negatively affect them. The difference in coefficient estimates between *FEMALE\_MP* and *MALE\_MP* shows that funds with a female MP experience 5.1% better annual flows. Therefore, the superior outcomes for female CPs are unlikely to be caused by their higher likelihood of being dedicated marketers.

Secondly, in approximately 9% of observations, all the CPs simultaneously serve as PMs. For the

same reasons as before – divided focus and lack of specialization – PMs who double as CPs may be poor fundraisers. Since PMs are mostly male, the challenges associated with these dual roles may disproportionately affect male CPs. To address this issue, we add an indicator variable, *CPisPM*, in Columns (3) and (4). This variable equals 1 if all of a fund’s CPs are PMs, and 0 otherwise. In Columns (5) and (6), we exclude all observations for which *CPisPM* is true. The positive effect of female CPs, measured by the variable *FEMALE\_CP*, is robust.

### 3.5.2 Due diligence story

Are women more successful because they can better predict the asset-growth potential of a fund? To investigate, we conduct tests to determine: (1) whether funds with female CPs exhibit better subsequent performance; and (2) whether strategies of funds with female CPs enjoy greater aggregate demand.

For (1), we rerun the regression in Equation 3.5 using various measures of future fund performance as the dependent variable. The results, shown in Panel A of Table 3.7, do not support the “due diligence story”: we find no evidence that funds with female CPs outperform others (rather the opposite). Interestingly, Columns (5) to (7) reveal an underperformance of funds with dedicated marketers. For instance, annual returns (*RET12*) for funds with female MPs (male MPs) are  $-1.24\%$  ( $-1.34\%$ ) lower than for those without.<sup>14</sup>

For (2), we use aggregate strategy demand as the dependent variable, proxied by the average flows into hedge funds that follow the same investment style (“Directional Traders”, “Relative Value”, etc.) or the same investment strategy (“Long/Short Equity”, “Event Driven”, etc.) as the fund in question.<sup>15</sup> The results are shown in Columns (1) to (4) and (5) to (8) of Panel B in Table 3.7, respectively. Again, we find no statistically significant evidence that funds with female CPs or MPs subsequently experience better aggregate flows at the style or the more granular strategy level. Importantly, the relationship is endogenous, as female CPs and MPs have a positive effect on flows into their own funds (and may have a negative effect on flows into competing funds). The statistically insignificant better flows into styles and strategies with female CPs and MPs are consistent with the interpretation that these individuals influence flows – rather than predict them.

Taken together, we find no evidence that the better fundraising success of female CPs is due to superior forecasting skills. We use performance and strategy demand as proxies for any fund-specific and economy-wide factors that determine the marketability of the fund, respectively. We use these proxies because they are observable, reasonably exogenous<sup>16</sup>, and strong predictors of fund flows. However, our analysis is necessarily limited, because we cannot rule out the possibility that women better predict the marketability of a fund in terms of other, unobserved characteristics, and that this ability is uncorrelated with the ability to predict fund performance or strategy demand. While performance is a useful proxy, it

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<sup>14</sup>An *ad hoc* explanation posits that (lucky) low-skilled managers hire marketers to “capitalize” quickly on past performance, while high-skill managers can afford to wait for the flow-performance relationship to take effect, and save on the costs of a marketer. In line with this interpretation, we later find that older funds are less likely to hire a CP or MP – see the *FAGE* coefficient in Panel A of Table 3.8 for CPs; this also holds for MPs in Panel B (not reported).

<sup>15</sup>We exclude funds of hedge funds (FoHFs) on the grounds that they represent a distinct class of funds with a separate investor base. The results are qualitatively unchanged if we include FoHFs or analyze FoHFs in isolation.

<sup>16</sup>CPs may benefit fund performance, for example, by assuming responsibility for “investor relations” tasks, thereby allowing the portfolio manager to focus on fund management. However, we see no intuitive argument to suggest a differential effect on fund performance between male and female CPs.

may not fully capture all relevant aspects of a fund’s potential attractiveness to investors. For example, women may more accurately judge the intelligence (Murphy et al., 2003) and personality (Chan et al., 2011) of portfolio managers.<sup>17</sup>

### 3.5.3 Career mobility story

Do female CPs raise more assets because they happen to work for the *ex ante* more attractive employers? To investigate, we analyze the determinants of CP turnover in a multinomial logistic regression framework. Our analysis is twofold: at the individual level, it examines the patterns of departures and hires among male and female CPs; at the fund level, it explores the factors influencing the replacement of female CPs with male CPs, and vice versa. As in Chapter 2, we extensively clean the events.<sup>18</sup> To obtain more reliable estimators and facilitate interpretation, we standardize non-dummy variables to unit variance. The analysis includes 886 CP hires (436 females and 450 males) and 909 CP departures (395 females and 514 males), 146 instances of a female CP replacing a male CP, and 128 instances of the opposite. We also include the event of fund closure (“Fund death”) as a plausibility check, given that the determinants of fund closure are well understood (Liang, 2000; Liang & Park, 2010).

We use fund performance as a proxy for other, unobserved fund characteristics desirable from the CP’s perspective, such as firm reputation and office location. Our reasoning is as follows: CPs, by virtue of their roles, have a vested interest in associating with well-performing funds, which are more promising in terms of career prospects, reputation, and compensation. They want to avoid reputational damage that could arise from prolonged association with underperforming funds. If female CPs are able to navigate their careers towards high-performing funds – potentially due to preferential hiring practices or their own strategic career choices – they may also be able to access funds that excel in other characteristics relevant for attracting flows.

Table 3.8 reveals that women indeed tend to engage with more desirable employers. In the regression on the left of Panel A, we find that a higher CAPM alpha rank in the past 12 months (*RANK\_CA12*) increases the odds of departure for male CPs but reduces the odds of a departure for female CPs. Specifically, for men (the baseline group), a one standard-deviation increase in *RANK\_CA12* over the last 12 months (given the other variables in the model are held constant) increases the odds of a departure by 7.1 percentage points (pp) ( $= \exp(0.069) - 1$ ). In contrast, for women, such an increase in rank is associated with a decrease in the odds of departure by 5.2 pp ( $= \exp(0.069 - 0.122) - 1$ ). The regression on the right extends the estimation window for flows and CAPM alpha rank to the prior 24 months, yielding statistically stronger results. These findings could be an artifact of the higher fraction of MPs among female CPs. It may not be women who work for well-performing funds, but rather MPs. To investigate, in Panel B of Table 3.8, we rerun the regressions in Panel A with a focus on MPs. The results differ, but still favor women: while a better CAPM rank increases the odds of joining for female MPs, it reduces

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<sup>17</sup>See Hall et al. (2016) for a literature survey on gender differences in interpersonal accuracy.

<sup>18</sup>Specifically, we manually ensure that each person is assigned a single name. As a result, spurious events caused by name changes (e.g., due to marriage) rather than actual changes in personnel are excluded. Additionally, we remove (1) events that are subsequently fully reversed, (2) hires of any person who departs again within 180 days, and (3) departures of persons who are subsequently rehired. Finally, we merge events that occur within 180 days of each other. For instance, if Person A is replaced by Person B, and Person B is then replaced by Person C within 180 days, we record the event as Person C replacing Person A.

them for male MPs.<sup>19</sup>

Panel C of Table 3.8 presents the results for the fund-level regressions. Similar to Table 3.5, we are interested in female CPs replacing male CPs (“Male → female CP”) and vice versa (“Female → male CP”). These events, while less frequent, allow to analyze the different career progressions of male and female CPs more directly. The results confirm the findings in Panel A, which suggested that female CPs have the intuitively more attractive careers. Specifically, a better ranking of the fund in terms of CAPM alpha increases the odds that a man is replaced by a woman, and vice versa for worse performance. However, only one of these coefficients is statistically significant. Taken together, the results provide evidence in favor of the career-mobility narrative.<sup>20</sup>

### 3.5.4 Attraction story

Do hedge funds with female contact persons receive higher net flows because male hedge fund investors are more emotionally inclined to engage with women? To test this fourth, “attraction” story, we examine whether flows into hedge funds (HFs) respond more strongly to the flows of funds of hedge funds (FoHF) when the FoHF portfolio manager (PM) is male, and the HF contact person (CP) is female. The premise of our analysis is that the capital allocation from FoHFs to HFs is so substantial that FoHF flows affect HF flows in an economically relevant manner. In support of this premise, EurekaHedge estimates that, at the end of April 2022, approximately 17% (USD 0.40 trillion (tn) out of USD 2.40tn) of HF AUM were allocated through FoHFs. Historically, this proportion has been even higher, reaching 23% in April 2015 (USD 0.50tn out of USD 2.22tn) and 43% in April 2008 (USD 0.82tn out of USD 1.90tn).<sup>21</sup> The decrease observed in recent years reflects growth in HF AUM alongside a reduction in FoHF AUM. Beyond the size of their allocations, FoHFs may cause a disproportionate amount of HF inflows and outflows due to their intermediary role. Their asset base is likely more volatile and their buying and selling of fund shares more active than that of direct, more passive HF investors such as pensions, insurances, or family offices. Moreover, the flows of FoHFs and HFs are likely to correspond, because the average cash position in FoHFs is only 6.7% of AUM, as Agarwal et al. (2019) infer from regulatory filings. We consider this low, because fees and other fund costs continuously deplete cash and therefore require maintaining a positive cash position. Thus, we argue that FoHF flows are relevant for HF flows.

Matching the flows of HFs and FoHFs presents a challenge. We make three decisions. First, we examine quarterly and semi-annual flows, because monthly flows are “very noisy” (Yin, 2016, p. 7) and annual flows would provide insufficient statistical power. Second, we focus on the 88% of HFs and 90% of FoHFs with monthly subscription frequency. HFs and FoHFs with higher subscription frequency are uncommon and often belong to distinct categories of funds.<sup>22</sup> Third, we omit a minority of HFs (2%) with

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<sup>19</sup>Interestingly, in both Panels A and B, we obtain the intuitively plausible result that better flows decrease the probability of CPs and MPs joining or leaving.

<sup>20</sup>The higher likelihood of departure after negative fund performance could also result from women being fired. However, additional, unreported results indicate no difference between male and female CPs’ turnover events in response to flows. We would expect such differences if women were evaluated more harshly, assuming that CPs are judged based on the flows they generate rather than fund performance.

<sup>21</sup>The data on FoHF AUM are taken from issues of the “EurekaHedge Report” for June 2009 (p. 13), May 2016 (p. 20), and June 2022 (p. 22). Industry AUM are from the EurekaHedge “Monthly GHF Asset Flow Region” table from October 2022.

<sup>22</sup>An example are hedge funds in compliance with the UCITS regulation (Joenväärä & Kosowski, 2021).

redemption notice periods equal to or longer than the longest redemption notice period observed among all FoHFs (120 days), given that investing in these HF would cause a liquidity mismatch for the FoHFs.<sup>23</sup>

To investigate whether male FoHF PMs gravitate towards HF with female CPs, we regress quarterly HF flows on simultaneous quarterly FoHF flows:

$$\begin{aligned}
 HF\_FLOW_{i,t} = & \beta_1 FEMALE\_CP_{i,t} \times MALE\_FOF\_FLOW_t \\
 & + \beta_2 FEMALE\_CP_{i,t} \times FEM\_FOF\_FLOW_t \\
 & + \sum_j \beta_3^j TIME\_VAR\_CTRLS_{i,t}^j + \sum_k \beta_4^k TIME\_INV\_CTRLS_i^k.
 \end{aligned} \tag{3.6}$$

Here, *TIME\_VAR\_CTRL*s and *TIME\_INV\_CTRL*s are time-varying and time-invariant control variables, respectively. *HF\_FLOW*<sub>*i,t*</sub> is the flow of HF *i* in the calendar quarter from month *t* to *t* + 3:

$$HF\_FLOW_{i,t} = \frac{AUM_{i,t+3}}{AUM_{i,t}} - (1 + RET_{i,t+1})(1 + RET_{i,t+2})(1 + RET_{i,t+3}), \tag{3.7}$$

where *t* can be March, June, September, or December. *AUM*<sub>*i,t*</sub> are the AUM of HF *i* at the end of month *t*, and *RET*<sub>*i,t*</sub> is its net return during the month. We set flows to zero if there is no change in AUM (when *AUM*<sub>*i,t+3*</sub> = *AUM*<sub>*i,t*</sub>).<sup>24</sup> *MALE\_FOF\_FLOW* and *FEM\_FOF\_FLOW* are the average quarterly flows of FoHFs managed exclusively by male and female PMs, respectively. The FoHF flows are calculated analogously to *HF\_FLOW*. The control variables are the same as in Equation 3.5, with the natural exception of time fixed effects.

The results reported in Table 3.9 indicate that male-managed FoHFs invest more strongly in HF with female CPs than female-managed FoHFs. Specifically, in Column (1) and (2), the positive coefficient estimate for the interaction *FEMALE\_CP* × *MALE\_FOF\_FLOW* suggests that flows from FoHFs led by male PMs have a more positive effect on the flows of HF if the HF’s CPs are female. In contrast, the insignificant coefficient for *FEMALE\_CP* × *FEM\_FOF\_FLOW* provides no evidence that the relationship between the aggregate flows of female-led FoHFs and HF flows varies with CP gender. The difference between the two interaction terms is statistically significant in Column (1) ( $\chi^2 = 3.28$ ) but insignificant in Column (2). Columns (3) and (4) explore the effect of dedicated marketers. We find that the differences in coefficients are economically stronger and both statistically significant at the 5% level.

In Columns (5) and (6), we narrow our focus to the subset of HF with quarterly redemption frequency. We anticipate stronger results from this subset, because FoHFs investing in quarterly HF should be more likely to align redemption dates. For example, if a FoHF needs to fulfill a redemption request set for March 31, we argue that the FoHF is likely to redeem from a target HF also on March 31, resulting in simultaneous outflows from both the HF and the FoHF in April (Q2).<sup>25</sup> Conversely, if the HF allows

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<sup>23</sup>A liquidity mismatch arises if a FoHF’s redemption notice period is shorter than that of its target HF, potentially preventing the FoHF from fulfilling investor redemption requests on time. On the other hand, mechanisms such as gating provisions, hard lockups, and internal allocations (“skin in the game”) could enable FoHFs to navigate these mismatches. Our results are robust if we retain HF with notice periods of 120 days or longer.

<sup>24</sup>AUM values are often rounded or stagnant, which is why the adjustment for fund returns can cause spurious flows, especially when flows are calculated over shorter time horizons (e.g., quarterly instead of annually). The results are robust if flows without change in AUM are not set to zero.

<sup>25</sup>Aligning the redemption dates is only possible if the FoHF has a longer redemption notice period than the HF. We find evidence that this is indeed the case: on average, HF and FoHFs with monthly (quarterly) redemption frequency require 35 and 43 (54 and 68) days’ notice, respectively. (For completeness: the “settlement period” – the duration between the redemption date and the actual cash transfer – must also be longer for the FoHF than for the HF. Otherwise, the FoHF might have to resort to alternative mechanisms, such as “overdraft” loans, to manage liquidity.)

monthly redemptions, then the FoHF may have the option to redeem already by February 28, causing an outflow from the HF during March (in Q1). We find the expected result – an increase in the economic magnitude of the effects – for both CPs and MPs.

In Columns (7) and (8), we no longer require a FoHF to be exclusively managed by women for *FEM\_FOF\_FLOW* to be populated, thereby including FoHFs managed by a “mixed-gender” team, yielding similar results. In Columns (9) and (10), we conduct a robustness test by analyzing semi-annual flows (at a semi-annual frequency) instead of quarterly flows (at a quarterly frequency). This weakens the alignment between FoHF and HF flows, and the coefficient differences become statistically insignificant. In conclusion, our analysis suggests that, compared to female FoHF PMs, male FoHF PMs allocate more strongly to HFs with female CPs and MPs. Finally, while not the focus of this section, the positive coefficient estimates for *FEMALE\_CP* and *FEMALE\_MP* across all columns of Table 3.9 confirm that our main result – the beneficial effect of female CPs and MPs – also holds when flows are calculated over quarterly or semi-annual instead of annual horizons.

### 3.6 Conclusion

We document a bias among professional investors toward hedge funds with female investor contact persons (CPs). On average, hedge funds with female CPs receive 2% higher annual flows than those with male CPs. This bias is not explained by the fact that female CPs more often than male CPs hold job titles that suggest an exclusive focus on marketing. Instead, we identify two potential causes. First, higher career mobility: women better align their professional paths with more promising funds. Second, an emotional-attraction effect: relative to female fund of hedge fund (FoHF) portfolio managers, male FoHF portfolio managers tend to gravitate towards hedge funds with female CPs.

To provide replicable results and offer a starting point for further research, we include instructions on reproducing the main results using publicly available data. We encourage further research to examine the effects of physical attractiveness and the attractiveness stereotype – the tendency to ascribe positive traits to attractive people (Dion et al., 1972; Eagly et al., 1991). The commercial impact of this stereotype remains underexplored (Reingen & Kernan, 1993). It may be particularly strong in the hedge fund setting, given that investors are typically men, who are more susceptible to this stereotype (Downs & Abshier, 1982).

As a further point of consideration for future research on female hedge fund managers, we highlight that fund management companies often enter the names of marketing or back-office staff in the “Portfolio Manager” data field. This phenomenon occurs disproportionately often when a female name is entered. Our data suggest that 24% of female PMs reported to TASS hold a job title that contradicts a portfolio-management role. While not the focus of this chapter, we recommend that researchers account for the high percentage of mislabeled female portfolio managers, especially when comparing the performance of male and female hedge fund managers.

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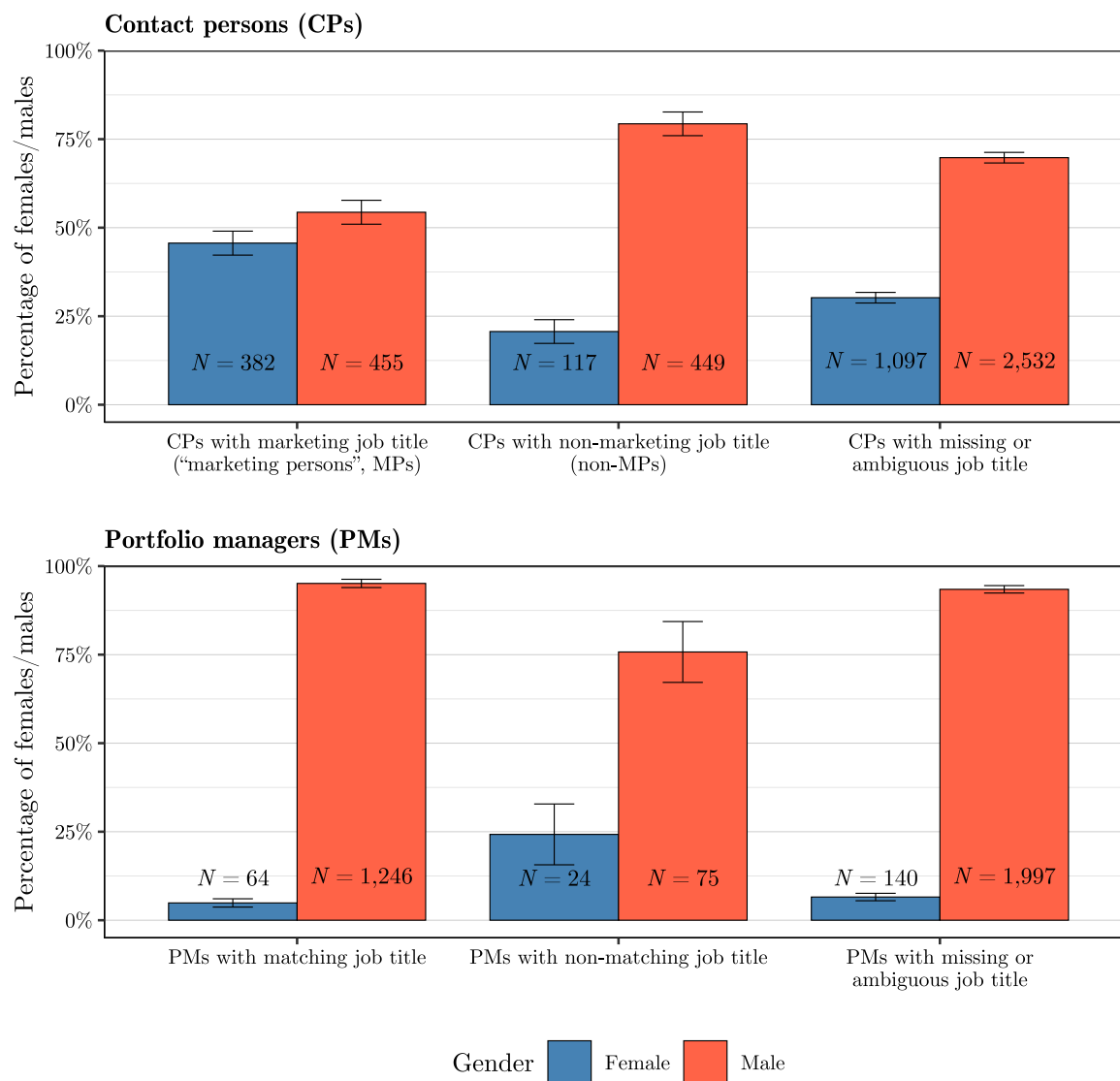
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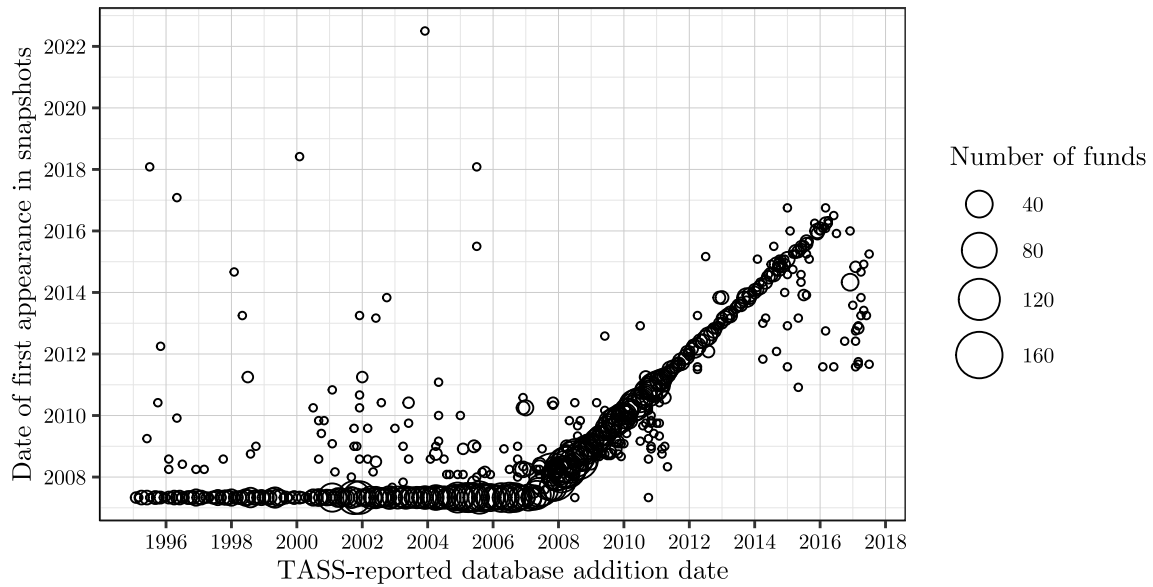
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## Figures

**Figure 3.1:** Gender distribution of hedge fund employees across job groups



*Note.* Illustrating data from Table 3.2, this figure shows the gender distribution across different job groups of contact persons (CPs) and portfolio managers (PMs) at hedge funds. CPs and PMs are hedge fund employees reported to TASS with “Person Type” “Marketing” and “Portfolio Manager”, respectively. Using TASS’s job titles, we categorize CPs as “marketing persons” (MPs) for those with explicitly marketing-related titles (such as “Investor Relations”) and as non-MPs for those with unrelated roles (such as “COO”), as detailed in Appendix 3.A.1. Similarly, PMs are classified based on the congruence of their job titles with traditional portfolio management roles. A third category comprises CPs and PMs with missing or vague job titles, such as “Director”. The error bars represent 95% confidence intervals for the estimated percentages of females and males.

**Figure 3.2:** Backfill bias: TASS addition dates versus first appearance in snapshots

*Note.* The figure compares the TASS-reported database addition dates of hedge funds (shown on the x-axis) with the dates of their initial appearances in our collection of historical TASS snapshots (represented on the y-axis). The close correlation between the addition and first-appearance dates after April 2007 validates our approach to infer missing database addition dates from first-appearance dates. The database addition dates are used to remove “backfilled” returns. The subsample includes all 5,644 hedge funds in our sample (out of a total of 6,301) for which TASS reports a database addition date. The snapshots span from April 2007 to January 2024.

## Tables

**Table 3.1:** Availability of historical TASS versions

This table summarizes the availability of historical versions (“snapshots”) of the TASS database. A cell is marked with a “Y” if at least one snapshot is available for the month. We use these snapshots to determine the employment histories of hedge fund employees.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2007	—	—	—	Y	Y	Y	Y	Y	Y	Y	Y	Y	9
2008	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2009	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2010	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2011	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2012	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2013	—	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	11
2014	Y	Y	—	Y	—	Y	Y	Y	Y	Y	Y	—	9
2015	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2016	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2017	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	—	—	10
2018	Y	—	Y	Y	Y	—	—	Y	Y	Y	Y	—	8
2019	Y	Y	Y	Y	—	Y	Y	—	Y	—	Y	Y	9
2020	—	Y	—	—	Y	—	Y	Y	Y	Y	—	Y	7
2021	—	—	Y	—	Y	Y	Y	Y	Y	Y	Y	Y	9
2022	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	—	Y	11
2023	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	12
2024	Y	—	—	—	—	—	—	—	—	—	—	—	1
Total	14	14	14	15	15	15	16	16	17	16	14	14	180

**Table 3.2:** Gender distribution of hedge fund employees by job title

The table reports the gender distribution of contact persons (CPs) and portfolio managers (PMs) by job title. CPs and PMs are hedge fund employees reported to TASS with “Person Type” “Marketing” and “Portfolio Manager”, respectively.

<b>Employee group</b>	<i>N</i>	<i>N</i>	% female	% female	Difference
— Job title	female	male	in role	overall	(role – overall)
<b>Contact persons (CPs)</b>					
<i>Job titles of CPs classified as MPs</i>					
— Marketing	62	83	42.8%	31.7%	11.0%***
— Director of Marketing	28	64	30.4%	31.7%	–1.3%
— Investor Relations	45	21	68.2%	31.7%	36.5%***
— Investment Relations	32	25	56.1%	31.7%	24.4%***
— Other MP titles	215	262	45.1%	31.7%	13.4%***
Total CPs with MP titles	382	455	45.6%	31.7%	13.9%***
<i>Job titles of CPs classified as non-MPs</i>					
— Portfolio Manager	5	103	4.6%	31.7%	–27.1%***
— COO	13	59	18.1%	31.7%	–13.7%**
— CFO	7	56	11.1%	31.7%	–20.6%***
— CIO	3	45	6.3%	31.7%	–25.5%***
— Other non-MP titles	89	186	32.4%	31.7%	0.6%
Total CPs with non-MP titles	117	449	20.7%	31.7%	–11.0%***
<i>Job titles of unclassified CPs</i>					
— (None or missing)	928	1,753	34.6%	31.7%	2.9%***
— Managing Director	19	133	12.5%	31.7%	–19.2%***
— Director	17	93	15.5%	31.7%	–16.3%***
— President	8	84	8.7%	31.7%	–23.0%***
— Other ambiguous titles	125	469	21.0%	31.7%	–10.7%***
Total unclassified CPs	1,097	2,532	30.2%	31.7%	–1.5%***
Total CPs	1,596	3,436	31.7%	31.7%	
<b>Portfolio managers (PMs)</b>					
<i>Job titles of correctly labeled PMs</i>					
— Portfolio Manager	44	833	5.0%	6.4%	–1.4%*
— CIO	11	212	4.9%	6.4%	–1.5%
— Fund Manager	4	96	4.0%	6.4%	–2.4%
— Senior Portfolio Manager	3	42	6.7%	6.4%	0.2%
— Other titles of correctly labeled PMs	2	63	3.1%	6.4%	–3.4%
Total correctly labeled PMs	64	1,246	4.9%	6.4%	–1.5%***
<i>Job titles of mislabeled PMs</i>					
— Marketing	5	10	33.3%	6.4%	26.9%***
— COO	1	10	9.1%	6.4%	2.7%
— CFO	0	10	0.0%	6.4%	–6.4%
— Marketing Director	1	5	16.7%	6.4%	10.2%
— Other titles of mislabeled PMs	17	40	29.8%	6.4%	23.4%***
Total mislabeled PMs	24	75	24.2%	6.4%	17.8%***
<i>Job titles of unclassified PMs</i>					
— (None or missing)	85	1,008	7.8%	6.4%	1.3%**
— Managing Director	5	130	3.7%	6.4%	–2.7%
— President	3	115	2.5%	6.4%	–3.9%
— Chief Executive Officer	4	105	3.7%	6.4%	–2.8%
— Other ambiguous titles	43	639	6.3%	6.4%	–0.1%
Total unclassified PMs	140	1,997	6.6%	6.4%	0.1%
Total PMs	228	3,318	6.4%	6.4%	0.0%

**Table 3.3:** Summary statistics

*Note:* This table summarizes the sample used in this Chapter 3. It consists of data for 6,301 USD-denominated hedge funds and funds of hedge funds from May 2005 to December 2023. Panel A reports the distribution of the main variables used in this study:

- Time-varying variables: These variables are summarized using fund-specific averages. *FEMALE\_CP* indicates whether all of a fund’s contact persons (CPs) are female. *FEMALE\_PM* indicates whether all its portfolio managers (PMs) are female. *FEMALE\_MP* and *MALE\_MP* indicate whether all of the CPs that could be identified as marketing persons (MPs) are female or male, respectively. *AUM* are fund assets under management, in USD million. *CA12* and *FH12* are CAPM alpha and Fung and Hsieh (2004) 7-factor alpha, respectively, where the factor loadings are estimated over 24-month windows and the average monthly alphas are calculated over the last 12 months of each window. *CPisPM* indicates whether all of the fund’s CPs are PMs. *FAGE* is the fund’s age since its inception, in years. *FLOW12* are fund flows over the prior 12 months. *RET12* and *SD12* denote cumulative net (after-fee) fund returns and their standard deviation, respectively, calculated over the prior 12 months. For exposition purposes, *CA12*, *FH12*, *FLOW12*, *RET12*, and *SD12* are expressed as percentages.
- Time-invariant variables: *BROKER* indicates whether the fund uses a blue-chip prime broker (see Footnote 12). *MFEE* and *IFEE* are the annual management and performance fee charged by the hedge fund, respectively. *HWM* indicates whether the performance fee is subject to a high-water-mark provision. *LEVERED* indicates whether the fund employs leverage. *LOCKUP* is the minimum initial investment duration, in months. *MININV* is the minimum initial investment amount, in USD million. *ONSHORE* indicates whether the fund is domiciled in the US. *PCAP* indicates whether the manager has personal capital invested in the fund. *REDFREQ* (redemption frequency) and *REDNOTI* (redemption notice) are the duration between two consecutive redemption dates and the advance notice period, respectively, each in days. *REST* (restriction period) is the sum of *REDFREQ* and *REDNOTI* (Agarwal et al., 2024; Aggarwal & Boyson, 2016).

Panel B reports the number of funds by year and employee structure. Panel C compares funds by CP gender. The main variable of interest is “*FLOW12* (next 12 months) (%)”, representing flows over the upcoming 12 months. To improve comparability across groups, we restrict the sample in Panel C to observations where this variable is populated. Significance levels are denoted as follows: \* for 10%, \*\* for 5%, and \*\*\* for 1%.

**Panel A:** Distribution of main fund variables

Variable	<i>N</i> funds	<i>N</i> observ.	Mean	SD	1st perc.	50th perc.	99th perc.
<i>Time-varying variables</i>							
<i>FEMALE_CP</i>	6,299	330,279	0.322	0.436	0.000	0.000	1.000
<i>FEMALE_PM</i>	6,299	330,279	0.028	0.160	0.000	0.000	1.000
<i>FEMALE_MP</i>	3,207	150,055	0.259	0.430	0.000	0.000	1.000
<i>MALE_MP</i>	3,207	150,055	0.297	0.450	0.000	0.000	1.000
<i>AUM</i>	6,301	324,475	210.070	1,519.395	1.000	44.606	2,305.097
<i>CA12</i> (%)	4,949	276,024	-0.064	0.966	-3.172	-0.021	2.215
<i>CPisPM</i>	6,299	330,279	0.083	0.261	0.000	0.000	1.000
<i>FAGE</i>	6,301	434,758	6.412	5.035	0.580	5.002	23.142
<i>FH12</i> (%)	4,949	276,024	0.087	1.020	-2.905	0.103	2.633
<i>FLOW12</i> (%)	4,626	212,613	3.648	45.194	-69.214	-3.063	208.544
<i>RET12</i> (%)	5,671	314,972	2.939	12.296	-31.866	3.228	36.740
<i>SD12</i> (%)	5,671	314,972	3.198	2.610	0.338	2.466	12.957
<i>Time-invariant variables</i>							
<i>BROKER</i>	6,301	6,301	0.411	0.492	0.000	0.000	1.000
<i>MFEE</i>	6,292	6,292	0.015	0.006	0.000	0.015	0.030
<i>IFEE</i>	6,270	6,270	0.151	0.078	0.000	0.200	0.250
<i>HWM</i>	6,301	6,301	0.721	0.448	0.000	1.000	1.000
<i>LEVERED</i>	6,301	6,301	0.539	0.498	0.000	1.000	1.000
<i>LOCKUP</i>	6,301	6,301	3.734	7.433	0.000	0.000	36.000
<i>MININV</i>	6,262	6,262	1.400	9.198	0.000	0.500	10.000
<i>ONSHORE</i>	6,301	6,301	0.319	0.466	0.000	0.000	1.000
<i>PCAP</i>	6,301	6,301	0.238	0.426	0.000	0.000	1.000
<i>REDFREQ</i>	6,140	6,140	69.070	80.155	1.000	30.000	360.000
<i>REDNOTI</i>	6,301	6,301	42.889	33.747	0.000	30.000	180.000
<i>REST</i>	6,140	6,140	112.933	95.971	2.000	90.000	450.000

**Panel B:** Number of funds by year and employee characteristics

	Per the end of								
	2007	2009	2011	2013	2015	2017	2019	2021	2023
<i>Contact persons (CPs)</i>									
Number of funds	2,521	2,610	2,602	2,042	1,901	931	620	414	312
- with one CP	2,007	2,247	2,265	1,828	1,718	842	550	365	276
o female	628	787	840	651	629	321	218	140	105
o male	1,379	1,460	1,425	1,177	1,089	521	332	225	171
- with two CPs	514	363	337	214	183	89	70	49	36
o both female	38	28	49	24	17	5	5	2	1
o both male	241	147	109	63	63	38	34	26	18
o mixed	235	188	179	127	103	46	31	21	17
<i>Portfolio managers (PMs)</i>									
Number of funds	2,521	2,610	2,602	2,042	1,901	931	620	414	312
- without PM	245	966	952	708	642	295	191	115	82
- with one PM	1,584	1,239	1,293	1,129	1,079	520	339	241	185
- with two PMs	464	293	261	150	135	93	72	49	36
- with three PMs	174	86	76	41	39	21	16	7	7
- with four PMs	37	15	13	11	3	1	2	2	2
- with five PMs	17	11	7	3	3	1	0	0	0

Panel C: Fund characteristics by contact person status

Variable	Funds' contact persons are...			Difference		
	...female (A)	...male (B)	...mixed (C)	A – B	A – C	B – C
<i>Time-varying variables</i>						
<i>FEMALE_PM</i>	0.031	0.017	0.033	0.013***	–0.002	–0.016***
<i>AUM</i>	329.983	242.567	338.926	87.416***	–8.943	–96.359***
<i>CA12</i> (%)	0.109	0.153	0.156	–0.044**	–0.047	–0.003
<i>CPisPM</i>	0.009	0.139	0.009	–0.130***	0.001	0.131***
<i>FAGE</i>	8.834	8.920	10.621	–0.087	–1.787***	–1.701***
<i>FH12</i> (%)	0.239	0.267	0.299	–0.027	–0.060*	–0.032
<i>FLOW12</i> (%)	6.193	4.470	3.957	1.724	2.237	0.513
<i>FLOW12</i> (next 12 months) (%)	1.399	–0.424	–2.371	1.823*	3.770**	1.947
<i>RET12</i> (%)	5.285	6.857	6.374	–1.572***	–1.089*	0.482
<i>SD12</i> (%)	2.917	3.202	2.667	–0.285***	0.250***	0.535***
<i>Time-invariant variables</i>						
<i>BROKER</i>	0.425	0.437	0.415	–0.011	0.010	0.022
<i>MFEE</i>	0.015	0.014	0.014	0.000	0.000	0.000
<i>IFEE</i>	0.145	0.156	0.158	–0.011***	–0.012***	–0.001
<i>HWM</i>	0.699	0.766	0.747	–0.067***	–0.048*	0.020
<i>LEVERED</i>	0.531	0.566	0.609	–0.035**	–0.078***	–0.043
<i>LOCKUP</i>	3.717	4.128	3.798	–0.410*	–0.081	0.330
<i>MININV</i>	1.231	1.209	1.499	0.022	–0.268	–0.290
<i>ONSHORE</i>	0.280	0.378	0.275	–0.098***	0.005	0.103***
<i>PCAP</i>	0.214	0.291	0.348	–0.076***	–0.133***	–0.057**
<i>REDFREQ</i>	67.076	70.616	74.336	–3.540	–7.260	–3.720
<i>REDNOTI</i>	44.871	44.270	45.849	0.601	–0.978	–1.579
<i>REST</i>	112.587	115.527	120.811	–2.940	–8.224	–5.284
<i>N observations</i>	5,147	9,742	1,058			

**Table 3.4:** Regressions on hedge fund flows

*Note.* This table presents the results of multivariate linear regressions examining the impact of female contact persons (CPs) on hedge fund flows. The dependent variable are hedge fund flows over the following 12 months ( $FLOW12(t + 12)$ ). The independent variables of interest are  $FEMALE\_CP$  and  $FEMALE\_CP\_PERC$ .  $FEMALE\_CP$  indicates whether the fund's CPs are exclusively female.  $FEMALE\_CP\_PERC$  represents the proportion of women among the fund's CPs.  $RANK\_CA12$ ,  $RANK\_FH12$ , and  $RANK\_RET12$  are the CAPM alpha, Fung and Hsieh (2004) alpha, and cumulative-return rank based on the previous 12 months. AUM are expressed in USD million. The additional fund control variables, detailed in the notes to Table 3.3, comprise  $BROKER$  (blue-chip prime broker),  $MFEE$  (management fee),  $IFEE$  (incentive fee),  $HWM$  (high-water mark),  $LOCKUP$  (lockup period),  $LEVERED$  (leverage indicator),  $FAGE$  (fund age),  $\log(REST)$  (restriction period),  $\log(MININV)$  (minimum investment),  $PCAP$  (personal-capital indicator), and  $ONSHORE$  (fund domicile). All regressions include fixed effects for investment style and year-month. Standard errors are clustered by fund and year-month;  $t$ -statistics are in parentheses. The sample consists of observations at annual intervals from April 2007 to December 2023. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels.

	Dependent variable: $FLOW12(t + 12)$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					$AUM \geq \text{USD } 25\text{m}$		$FLOW12 < 0$	$FLOW12 \geq 0$	No FoHF	
$FEMALE\_CP$	0.020** (2.002)	0.020** (2.018)	0.018* (1.693)	0.032*** (3.300)	0.018 (1.638)	0.019* (1.686)	-0.002 (-0.318)	0.053** (2.298)	0.024** (2.113)	
$FEMALE\_CP\_PERC$										0.020** (2.003)
$FEMALE\_PM$	0.057** (2.013)	0.048* (1.802)	0.049* (1.833)	0.045** (2.036)	0.015 (0.505)	0.008 (0.294)	-0.001 (-0.039)	0.019 (0.285)	0.051 (1.417)	0.030 (1.384)
$RANK\_CA12$	0.325*** (16.136)	0.311*** (15.445)			0.341*** (15.739)	0.327*** (15.748)	0.085*** (8.149)	0.169*** (4.275)	0.305*** (14.874)	0.317*** (15.274)
$RANK\_FH12$			0.284*** (12.285)							
$RANK\_RET12$				0.347*** (14.957)						
$\log(AUM)$	-0.029*** (-7.046)	-0.031*** (-8.270)	-0.030*** (-7.929)	-0.036*** (-8.551)	-0.016*** (-3.591)	-0.019*** (-4.871)	-0.016*** (-7.694)	-0.043*** (-5.533)	-0.032*** (-6.515)	-0.031*** (-8.474)
Add. fund controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
FE (style, YM)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,697	11,476	11,476	13,089	9,084	8,933	7,595	3,881	8,768	12,423
Adj. $R^2$	0.071	0.079	0.073	0.091	0.082	0.089	0.112	0.066	0.078	0.079
Within adj. $R^2$	0.046	0.053	0.046	0.062	0.049	0.056	0.061	0.039	0.052	0.052

**Table 3.5:** Event study around changes in contact person gender

*Note:* The table presents the results of a difference-in-differences analysis examining the effect of changes in the gender composition of hedge fund CPs on investor capital flows. Group (1) includes funds that increase (“↑”), and group (2) includes funds that decrease (“↓”) the percentage of female CPs (*FEM\_CP\_PERC*). Funds in group (3) undergo a change in CP that does not affect *FEM\_CP\_PERC*. The variable *FLOW12* represents hedge fund flows over 12-month intervals. The event-window length varies between 12, 24, and 36 months. For example, in the second specification of Panel A (“Event window = 24 months”), the column “before” (“after”) refers to the two 12-month periods preceding (following) the CP turnover. Observations must have data for both the “before” and “after” periods to be included in the analysis. For Panel B, flows are estimated and observed at semi-annual intervals instead of annual intervals. The sample covers the period from April 2007 to December 2023.

**Panel A:** Flows over 12-month periods (*FLOW12*)

	<i>N</i>	Before	After	After – Before	<i>t</i> -statistic
Event window = 12 months					
(1) <i>FEM_CP_PERC</i> ↑	158	0.054	−0.036	−0.090	−1.441
(2) <i>FEM_CP_PERC</i> ↓	134	0.107	−0.185	−0.292***	−5.035
(3) <i>FEM_CP_PERC</i> uch.	313	0.043	−0.001	−0.044	−0.930
Difference (1) – (2)				0.202**	2.363
Event window = 24 months					
(1) <i>FEM_CP_PERC</i> ↑	244	0.090	−0.018	−0.108**	−2.023
(2) <i>FEM_CP_PERC</i> ↓	204	0.130	−0.157	−0.287***	−6.238
(3) <i>FEM_CP_PERC</i> uch.	475	0.050	−0.007	−0.057	−1.606
Difference (1) – (2)				0.179**	2.529
Event window = 36 months					
(1) <i>FEM_CP_PERC</i> ↑ group	294	0.082	−0.002	−0.084*	−1.675
(2) <i>FEM_CP_PERC</i> ↓ group	236	0.116	−0.158	−0.274***	−6.483
(3) <i>FEM_CP_PERC</i> uch.	558	0.049	0.000	−0.049	−1.547
Difference (1) – (2)				0.189***	2.883

**Panel B:** Flows over 6-month periods (*FLOW6*)

	<i>N</i>	Before	After	After – Before	<i>t</i> -statistic
Event window = 12 months					
(1) <i>FEM_CP_PERC</i> ↑	421	0.014	−0.047	−0.061***	−2.840
(2) <i>FEM_CP_PERC</i> ↓	351	0.024	−0.074	−0.098***	−4.603
(3) <i>FEM_CP_PERC</i> uch.	822	0.018	−0.026	−0.044***	−2.772
Difference (1) – (2)				0.037	1.233
Event window = 24 months					
(1) <i>FEM_CP_PERC</i> ↑	648	0.029	−0.040	−0.069***	−3.929
(2) <i>FEM_CP_PERC</i> ↓	532	0.034	−0.068	−0.102***	−6.070
(3) <i>FEM_CP_PERC</i> uch.	1245	0.028	−0.021	−0.049***	−4.008
Difference (1) – (2)				0.032	1.329
Event window = 36 months					
(1) <i>FEM_CP_PERC</i> ↑	771	0.040	−0.034	−0.074***	−4.450
(2) <i>FEM_CP_PERC</i> ↓	617	0.032	−0.068	−0.101***	−6.577
(3) <i>FEM_CP_PERC</i> uch.	1490	0.035	−0.015	−0.050***	−4.415
Difference (1) – (2)				0.026	1.151

**Table 3.6:** “Job story”: regressions on hedge fund flows

*Note:* Closely following Table 3.4, this table presents the results of multivariate linear regressions examining the impact of female marketing persons (MPs) and female contact persons (CPs) on hedge fund flows. The dependent variable remains hedge fund flows over the following 12 months:  $FLOW_{12}(t+12)$ . Unlike Table 3.4, the key independent variables here are  $FEMALE\_MP$ ,  $MALE\_MP$ , and  $CPisPM$ .  $FEMALE\_MP$  and  $MALE\_MP$  indicate whether all MPs are female or male, respectively, while  $CPisPM$  denotes whether all CPs also act as portfolio managers (PMs). Columns (5) and (6) include only observations where  $CPisPM$  is false. Control variables, fixed effects, and standard errors are the same as in Table 3.4. The sample and time period also remain the same, covering April 2007 to December 2023. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $FLOW_{12}(t+12)$					
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>CPisPM</i> is false					
<i>FEMALE_MP</i>	0.034** (2.183)	0.027* (1.833)				
<i>MALE_MP</i>	-0.029* (-1.891)	-0.024* (-1.657)				
<i>FEMALE_CP</i>			0.022** (2.108)	0.022** (2.120)	0.022** (2.109)	0.023** (2.144)
<i>FEMALE_PM</i>	-0.009 (-0.241)	-0.021 (-0.592)	0.056** (2.004)	0.048* (1.793)	0.068** (2.342)	0.060** (2.205)
<i>CPisPM</i>			0.014 (0.955)	0.013 (0.940)		
<i>RANK_CA12</i>	0.319*** (13.586)	0.303*** (12.946)	0.324*** (16.131)	0.311*** (15.452)	0.341*** (15.775)	0.327*** (15.061)
$\log(AUM)$	-0.031*** (-5.470)	-0.031*** (-5.755)	-0.029*** (-6.789)	-0.031*** (-8.017)	-0.028*** (-6.447)	-0.030*** (-7.793)
<i>BROKER</i>		0.010 (0.776)		-0.007 (-0.644)		-0.002 (-0.152)
<i>MFEE</i>		-0.122 (-0.087)		0.890 (0.964)		1.286 (1.220)
<i>IFEE</i>		0.160 (1.181)		-0.085 (-0.868)		-0.107 (-1.039)
<i>HWM</i>		0.012 (0.637)		0.004 (0.317)		-0.001 (-0.070)
<i>LOCKUP</i>		0.000 (-0.442)		-0.001 (-1.452)		-0.001* (-1.667)
<i>LEVERAGE</i>		0.015 (0.977)		0.014 (1.596)		0.012 (1.324)
<i>FAGE</i>		-0.004*** (-3.119)		-0.005*** (-5.057)		-0.005*** (-4.668)
$\log(REST)$		-0.003 (-0.347)		0.009 (1.210)		0.012 (1.384)
$\log(MININV)$		0.007** (2.144)		0.012*** (3.514)		0.013*** (3.513)
<i>PCAP</i>		0.015 (1.095)		0.004 (0.377)		0.003 (0.335)
<i>ONSHORE</i>		-0.016 (-1.063)		-0.001 (-0.116)		0.001 (0.073)
FE (style, YM)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,047	5,999	11,697	11,476	10,495	10,277
Adj. $R^2$	0.074	0.078	0.071	0.079	0.073	0.081
Within adj. $R^2$	0.048	0.051	0.046	0.053	0.048	0.055

**Table 3.7:** “Due diligence story”: regressions on hedge fund performance and aggregate flows

*Note:* This table presents the results of multivariate linear regression analyses exploring the effect of female contact persons (CPs) and marketing persons (MPs) on hedge fund performance (Panel A) and on aggregate flows to hedge fund styles and strategies (Panel B). In Panel A, the dependent variables are average monthly CAPM alphas (*CA12*), average monthly Fung and Hsieh (2004) 7-factor alphas (*FH12*) or cumulative net fund returns (*RET12*), each calculated over the following 12 months. The regressions in Panel A include fixed effects for investment style and year-month. In Panel B, the dependent variable are average flows into hedge funds of the same style (Columns 1 to 4) or strategy (Columns 5 to 8), where strategy is more granular than style. In both Panels A and B, the additional fund control variables, detailed in the notes to Table 3.3, comprise  $\log(\text{AUM})$  (AUM), *BROKER* (blue-chip prime broker), *MFEE* (management fee), *IFEE* (incentive fee), *HWM* (high-water mark), *LOCKUP* (lockup period), *LEVERED* (leverage indicator), *FAGE* (fund age),  $\log(\text{REST})$  (restriction period),  $\log(\text{MININV})$  (minimum investment), *PCAP* (personal-capital indicator), and *ONSHORE* (fund domicile). Standard errors are clustered by fund and year-month. The sample consists of annual observations from April 2007 to December 2023. The dependent variables are expressed in percentages for exposition purposes.

**Panel A:** Regressions on fund performance

Dep. v. (all $t + 12$ ):	<i>CA12</i> (%)	<i>CA12</i> (%)	<i>RET12</i> (%)	<i>FH12</i> (%)	<i>CA12</i> (%)	<i>RET12</i> (%)	<i>FH12</i> (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>FEMALE_CP</i>	0.007 (0.265)	-0.001 (-0.040)	-0.413 (-1.630)	0.008 (0.298)			
<i>FEMALE_MP</i>					-0.102** (-2.458)	-1.243** (-2.324)	-0.090** (-2.074)
<i>MALE_MP</i>					-0.053 (-1.102)	-1.344** (-2.317)	-0.076* (-1.886)
<i>FEMALE_PM</i>	0.016 (0.251)	0.029 (0.412)	1.452* (1.932)	0.005 (0.077)	-0.178 (-1.428)	0.737 (0.491)	-0.095 (-0.802)
Add. fund controls	No	Yes	Yes	Yes	Yes	Yes	Yes
FE (style, YM)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,951	15,139	16,850	15,139	7,650	8,371	7,650
Adj. $R^2$	0.063	0.071	0.201	0.060	0.081	0.205	0.066
Within adj. $R^2$	0.000	0.006	0.006	0.007	0.008	0.006	0.009

**Panel B:** Regressions on style- and strategy-level flows

Dependent variable:	Average <i>FLOW12</i> ( $t + 12$ ) (%) to style				Average <i>FLOW12</i> ( $t + 12$ ) (%) to strategy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>FEMALE_CP</i>	-0.110 (-0.189)	0.070 (0.109)			0.469 (0.735)	0.661 (0.909)		
<i>FEMALE_MP</i>			-0.008 (-0.007)	0.645 (0.484)			0.405 (0.325)	1.011 (0.693)
<i>MALE_MP</i>			-0.105 (-0.119)	-0.119 (-0.136)			-0.887 (-0.847)	-0.981 (-0.865)
<i>FEMALE_PM</i>	-0.234 (-0.193)	-1.125 (-0.993)	2.186 (1.103)	0.752 (0.435)	-0.050 (-0.035)	-1.262 (-0.924)	1.869 (0.797)	-0.109 (-0.053)
Add. fund controls	No	Yes	No	Yes	No	Yes	No	Yes
FE	No	No	No	No	No	No	No	No
Observations	19,401	15,331	9,985	8,107	18,989	15,157	9,800	8,028
Adj. $R^2$	0.000	0.040	0.000	0.042	0.000	0.031	0.000	0.031

**Table 3.8:** “Career mobility story”: determinants of contact person turnover

*Note.* The table reports the results of multinomial logistic regressions exploring the determinants of turnover among hedge fund contact persons (CPs) and marketing persons (MPs). Panels A and B examine CP and MP turnover at the person level, respectively, while Panel C examines turnover at the fund level. Each panel consists of two regressions, where those titled “Prior 12 months” (“Prior 24 months”) include *FLOW12* and *RANK\_CA12* (*FLOW24* and *RANK\_CA24*) as independent variables. In Panels A and B, *FEMALE* is an indicator variable equal to 1 if the CP or MP is female and 0 if male. *CP\_AGE* is the estimated age of the person. The other independent variables are detailed in the note to Table 3.3. In Panel B, the additional fund controls, omitted for brevity, are the same as in Panel A ( $\log(AUM)$ , ..., *ONSHORE*). The sample consists of monthly observations from April 2007 to December 2023. Significance levels are denoted as follows: \* for 10%, \*\* for 5%, and \*\*\* for 1%.

**Panel A:** Regressions on person level: contact persons (CPs)

	Prior 12 months			Prior 24 months		
	CP joins	CP leaves	Fund death	CP joins	CP leaves	Fund death
<i>FLOW12</i>	-0.034 (-0.947)	-0.081** (-2.155)	-0.335*** (-9.256)	-0.042 (-1.222)	-0.048 (-1.410)	-0.180*** (-5.159)
<i>RANK_CA12 (24)</i>	0.000 (0.009)	0.069 (1.491)	-0.303*** (-10.744)	0.077 (1.499)	0.120** (2.519)	-0.365*** (-12.399)
<i>RANK_CA12 (24) × FEMALE</i>	0.077 (1.110)	-0.122* (-1.758)	-0.080 (-1.617)	0.045 (0.639)	-0.150** (-2.131)	-0.063 (-1.230)
<i>FEMALE</i>	0.411*** (2.837)	0.582*** (4.113)	0.050 (0.586)	0.511*** (3.370)	0.656*** (4.466)	0.033 (0.380)
log( <i>AUM</i> )	0.124*** (2.721)	0.127*** (2.824)	-0.384*** (-11.774)	0.095** (2.021)	0.131*** (2.843)	-0.363*** (-10.716)
<i>BROKER</i>	0.185** (2.340)	0.060 (0.775)	0.155*** (3.050)	0.168** (2.100)	0.023 (0.288)	0.159*** (3.067)
<i>MFEE</i>	0.049 (1.342)	0.034 (0.950)	0.072*** (3.063)	0.039 (1.022)	0.039 (1.090)	0.082*** (3.435)
<i>IFEE</i>	-0.092 (-1.632)	-0.079 (-1.405)	0.093** (2.506)	-0.081 (-1.402)	-0.081 (-1.423)	0.089** (2.351)
<i>HWM</i>	0.206** (2.118)	0.204** (2.148)	-0.062 (-1.012)	0.233** (2.347)	0.220** (2.285)	-0.044 (-0.695)
<i>LOCKUP</i>	-0.020 (-0.545)	-0.031 (-0.844)	-0.013 (-0.502)	-0.033 (-0.882)	-0.049 (-1.292)	-0.009 (-0.352)
<i>LEVERED</i>	-0.001 (-0.009)	0.018 (0.240)	-0.115** (-2.359)	0.030 (0.396)	0.063 (0.842)	-0.146*** (-2.914)
<i>FAGE</i>	-0.175*** (-3.455)	-0.077 (-1.590)	-0.183*** (-5.869)	-0.155*** (-2.990)	-0.073 (-1.466)	-0.186*** (-5.746)
<i>CP_AGE</i>	-0.061* (-1.699)	0.013 (0.377)	0.017 (0.706)	-0.092** (-2.544)	0.023 (0.644)	0.023 (0.927)
log( <i>REST</i> )	0.020 (0.464)	-0.023 (-0.560)	0.085*** (2.837)	0.050 (1.090)	-0.013 (-0.322)	0.078** (2.542)
log( <i>MININV</i> )	0.121** (2.549)	0.147*** (3.036)	0.232*** (6.440)	0.120** (2.467)	0.144*** (2.941)	0.246*** (6.568)
<i>PCAP</i>	-0.314*** (-3.949)	-0.231*** (-3.026)	-0.095* (-1.871)	-0.328*** (-4.086)	-0.250*** (-3.238)	-0.101* (-1.948)
<i>ONSHORE</i>	-0.093 (-1.168)	-0.153* (-1.942)	-0.108** (-2.089)	-0.101 (-1.244)	-0.167** (-2.094)	-0.125** (-2.375)
FE (year, style)	Yes			Yes		
Observations	169,485			162,782		
Number of events	886	909	2,013	861	889	1,916
Pseudo $R^2$	0.051			0.051		

**Panel B:** Regressions on personal level: marketing persons (MPs)

	Prior 12 months			Prior 24 months		
	MP joins	MP leaves	Fund death	MP joins	MP leaves	Fund death
<i>FLOW12</i>	-0.124*	-0.044	-0.490***	-0.113*	-0.154*	-0.187**
	(-1.749)	(-0.506)	(-5.951)	(-1.695)	(-1.655)	(-2.572)
<i>RANK_CA12 (24)</i>	-0.182**	-0.060	-0.315***	-0.073	0.070	-0.409***
	(-2.137)	(-0.468)	(-4.869)	(-0.826)	(0.533)	(-6.058)
<i>RANK_CA12 (24) × FEMALE</i>	0.355***	0.010	-0.129	0.222*	-0.171	-0.066
	(2.934)	(0.059)	(-1.281)	(1.811)	(-1.041)	(-0.641)
<i>FEMALE</i>	-0.576**	0.623*	0.019	-0.329	0.900***	-0.085
	(-2.248)	(1.857)	(0.107)	(-1.237)	(2.597)	(-0.481)
Add. fund controls	Yes			Yes		
FE (year, style)	Yes			Yes		
Observations	41,203			40,010		
Number of events	296	182	466	296	188	445
Pseudo- $R^2$	0.072			0.069		

**Panel C:** Regressions on fund level

	Prior 12 months			Prior 24 months		
	Male → female CP	Female → male CP	Fund death	Male → female CP	Female → male CP	Fund death
<i>FLOW12 (24)</i>	0.050	0.117	-0.331***	-0.006	0.041	-0.194***
	(0.657)	(1.484)	(-8.534)	(-0.080)	(0.473)	(-5.076)
<i>RANK_CA12 (24)</i>	0.055	-0.064	-0.317***	0.155*	-0.098	-0.373***
	(0.647)	(-0.682)	(-12.465)	(1.748)	(-0.959)	(-13.972)
$\log(AUM)$	0.048	0.029	-0.384***	-0.025	0.093	-0.363***
	(0.423)	(0.241)	(-10.857)	(-0.215)	(0.720)	(-9.810)
<i>BROKER</i>	0.280	-0.142	0.133**	0.287	-0.085	0.136**
	(1.504)	(-0.690)	(2.417)	(1.529)	(-0.386)	(2.418)
<i>MFEE</i>	0.060	0.095	0.061**	0.032	0.018	0.072***
	(0.633)	(1.031)	(2.381)	(0.334)	(0.174)	(2.764)
<i>IFEE</i>	0.000	-0.318**	0.104***	0.011	-0.355**	0.100**
	(-0.003)	(-2.246)	(2.587)	(0.072)	(-2.327)	(2.416)
<i>HWM</i>	0.540**	0.049	-0.040	0.489*	0.097	-0.029
	(1.964)	(0.199)	(-0.596)	(1.782)	(0.364)	(-0.416)
<i>LOCKUP</i>	0.029	0.021	-0.035	0.032	-0.013	-0.030
	(0.327)	(0.216)	(-1.243)	(0.356)	(-0.129)	(-1.058)
<i>LEVERED</i>	-0.172	0.290	-0.139***	-0.235	0.380*	-0.165***
	(-0.958)	(1.476)	(-2.651)	(-1.297)	(1.809)	(-3.045)
<i>FAGE</i>	-0.229*	-0.083	-0.197***	-0.242*	-0.100	-0.204***
	(-1.731)	(-0.643)	(-5.768)	(-1.781)	(-0.717)	(-5.759)
$\log(REST)$	-0.132	-0.050	0.084***	-0.129	0.183	0.078**
	(-1.340)	(-0.481)	(2.592)	(-1.265)	(1.400)	(2.347)
$\log(MININV)$	0.056	0.245*	0.210***	0.069	0.189	0.218***
	(0.455)	(1.838)	(5.502)	(0.544)	(1.346)	(5.496)
<i>PCAP</i>	-0.124	-0.555**	-0.076	-0.086	-0.580**	-0.067
	(-0.665)	(-2.529)	(-1.372)	(-0.460)	(-2.498)	(-1.187)
<i>ONSHORE</i>	-0.086	-0.115	-0.101*	-0.066	-0.171	-0.115**
	(-0.445)	(-0.556)	(-1.791)	(-0.342)	(-0.775)	(-2.004)
FE (year)	Yes			Yes		
Observations	145,941			140,192		
Number of events	146	128	1,717	143	113	1,626
Pseudo- $R^2$	0.047			0.048		

**Table 3.9:** “Attraction story”: influence of gender dynamics on hedge fund flows

*Note.* This table presents the results of multivariate linear regression analyses aimed at understanding the interaction between the genders of fund of hedge fund (FoHF) portfolio managers (PMs) and hedge fund (HF) contact persons (CPs) and marketing persons (MPs). The dependent variable are hedge fund flows (*HF\_FLOW*) over the next quarter (Columns 1 to 8) or half year (Columns 9 and 10). *FEMALE\_FOF\_FLOW* and *MALE\_FOF\_FLOW* are the average quarterly flows of FoHFs managed by female or male PMs, respectively. The additional fund control variables, omitted for brevity and detailed in the notes to Table 3.3, include *BROKER*, *MFEE*, *IFEE*, *HWM*, *LOCKUP*, *LEVERED*, *FAGE*,  $\log(\text{REST})$ ,  $\log(\text{MININV})$ , *PCAP*, and *ONSHORE*. Standard errors are clustered by fund and year-month; *t*-statistics are shown in parentheses,  $\chi^2$ -statistics in brackets. The sample consists of observations at quarterly (Columns 1 to 8) or semi-annual (Columns 9 and 10) intervals from April 2007 to December 2023.

	Dependent variable: <i>HF_FLOW</i>									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Only funds with quarterly redemption frequency	Include mixed teams in <i>FOF_FEM_FLOW</i>		Observation frequency and <i>HF_FLOW</i> semi-annual		
<i>FEMALE_CP</i> × <i>FOF_MALE_FLOW</i> (I)	0.157*	0.142*			0.204*		0.111		0.127*	
	(1.873)	(1.709)			(1.841)		(1.341)		(1.715)	
<i>FEMALE_CP</i> × <i>FOF_FEM_FLOW</i> (II)	-0.011	-0.007			0.005		-0.024		0.061	
	(-0.244)	(-0.157)			(0.071)		(-0.521)		(1.072)	
<i>FEMALE_CP</i>	0.010***	0.010***			0.016***		0.008**		0.018***	
	(2.835)	(2.924)			(2.797)		(2.540)		(3.879)	
<i>FEMALE_MP</i> × <i>FOF_MALE_FLOW</i> (I)			0.325	0.308		0.476		0.289		0.229
			(1.419)	(1.338)		(1.589)		(1.415)		(0.898)
<i>FEMALE_MP</i> × <i>FOF_FEM_FLOW</i> (II)			-0.090	-0.082		-0.085		-0.168*		0.003
			(-0.822)	(-0.764)		(-0.505)		(-1.918)		(0.021)
<i>FEMALE_MP</i>			0.018**	0.018**		0.030**		0.014*		0.040**
			(2.157)	(2.050)		(2.110)		(1.826)		(2.100)
<i>FOF_MALE_FLOW</i>	0.599***	0.607***	0.492**	0.509**	0.529***	0.445	0.564***	0.446**	0.489***	0.515*
	(3.367)	(3.404)	(2.011)	(2.064)	(3.386)	(1.521)	(3.280)	(2.020)	(3.116)	(1.940)
<i>FOF_FEM_FLOW</i>	-0.043	-0.044	0.082	0.081	0.026	0.114	-0.012	0.148*	-0.175*	-0.162
	(-0.699)	(-0.705)	(0.969)	(0.965)	(0.337)	(0.961)	(-0.185)	(1.820)	(-1.763)	(-1.202)
<i>FEMALE_PM</i>	0.002	0.002	-0.016	-0.013	0.005	-0.002	0.005	0.002	0.002	-0.042
	(0.235)	(0.205)	(-0.929)	(-0.868)	(0.445)	(-0.147)	(0.596)	(0.217)	(0.123)	(-1.191)
Constant	-0.033***	-0.069***	-0.048***	-0.075***	-0.042	-0.109	-0.065***	-0.068***	-0.125***	-0.150***
	(-3.875)	(-4.432)	(-3.764)	(-3.710)	(-0.606)	(-0.782)	(-4.358)	(-3.489)	(-3.448)	(-2.916)
Controls for <i>RANK_CA12</i> and $\log(\text{AUM})$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. fund controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,292	30,057	7,894	7,889	11,699	3,240	32,977	8,657	14,500	3,787
Adj. $R^2$	0.052	0.055	0.050	0.051	0.054	0.054	0.051	0.048	0.066	0.071
Difference (I) – (II)	0.168*	0.149	0.414**	0.390**	0.199	0.561**	0.135	0.457**	0.066	0.227
$\chi^2$ -statistic	[3.282]	[2.575]	[5.013]	[4.436]	[1.859]	[4.081]	[2.174]	[6.599]	[0.474]	[1.301]

### 3.A Appendix

#### 3.A.1 Identification of hedge fund marketers

This table shows how we categorize contact persons (CPs) at hedge funds as marketing persons (MPs) or non-MPs based on their job titles. For presentation purposes, the words “Vice President”, “Performance”, and “Development” are abbreviated as “VP”, “Perform.”, and “Developm.”, respectively. Other job titles are kept in the original, including any spelling errors (such as “client liason”).

CPs classified as MPs		CPs classified as non-MPs		Unclassified CPs	
Job title	Count	Job title	Count	Job title	Count
Marketing	145	Portfolio Manager	108	<i>(None or missing)</i>	2,681
Director of Marketing	92	COO	72	Managing Director	152
Investor Relations	66	CFO	63	Director	110
Investment Relations	57	CIO	48	President	92
Marketing Director	44	Analyst	45	Perform. Contact	78
Marketing Associate	41	Administrator	25	Principal	70
Marketing Manager	38	Operations Manager	25	Chief Executive Officer	56
Business Developm.	37	Fund Manager	21	VP	53
Investor Relations Manager	33	Senior Analyst	13	Managing Partner	48
Director of Business Developm.	29	Controller	12	Partner	44
Marketing/Client Services	19	Operations	12	Senior VP	35
Chief Marketing Officer	18	Director of Operations	8	Associate	34
Client Services Manager	18	Founder	8	Manager	27
Client Service	17	Perform. Data Analyst	8	Managing Member	27
Director of Client Services	17	Fund Administrator	7	General Partner	19
Marketing Executive	15	Administrative Assistant	6	Chairman and CEO	15
VP Marketing	15	Chief Portfolio Manager	6	Chairman	11
Marketing Assistant	13	Executive Assistant	6	Executive Director	11
Hedge Fund Marketing	11	Financial Analyst	6	Executive VP	8
Marketer	11	Investment Manager	6	Consultant	7
Product Manager	10	Senior Portfolio Manager	6	Adviser	6
Director Sales	8	Database Administrator	5	Assistant VP	6
VP Business Developm.	8	Chief Administrative Officer	4	Managing Member of the GP	6
Client Liason	7	Investment Analyst	4	Associate Director	5
Account Manager	6	Key Portfolio Manager	4	Managing Principal	5
Business Manager	6	President and CIO	4	President and CEO	5
Client Relations Analyst	6	Research Advisor	4	Investment Advisor	4
Director of Institutional Sales	6	Risk Management	4	Sr Assoc	4
VP Investor Relations	6	Account & Perform. Analyst	3	Assistant Manager	3
Manager of Client Services	5	Accountant Assistant	3	General Manager	2
Marketing Co-ordinator	5	Director of Research	3	Vice Chairman	2
Senior Marketing Associate	5	Head Trader	3	International Director	1
Marketing Consultant	3	Trader	3	Sr Managing Dir	1
Relationship Coordinator	3	Investment Team	2	Strategist	1
VP Institutional Sales	3	Chief Investment Strategist	1		
Assistant VP Marketing	2	Director of Trading	1		
Client Service Associate	2	Head Portfolio Manager	1		
Senior VP Business Developm.	2	Investment Officer (Europe)	1		
VP of Client Relations	2	Portfolio Administrator	1		
VP Sales	2	President CFO	1		
Account Executive	1	Secretary	1		
Director of Product Developm.	1	VP Administration	1		
Marketing Representative	1	VP Portfolio Manager	1		
Product Developm.	1				
<b>Total</b>	<b>837</b>		<b>566</b>		<b>3,629</b>

### 3.A.2 Replicable results

Hedge fund studies are often difficult to replicate. This chapter is no exception, as it relies on historical TASS versions, which are not commercially available. To provide reproducible results and a starting point for further research, we demonstrate how our main finding – the better flows into hedge funds with female contact persons (CPs) and female marketing persons (MPs) – can be replicated using a recent version of TASS. Specifically, for the results reported on the next page, the following steps have been applied to a March 2024 version of TASS that includes both live and dead funds:

**1. Data selection:**

Using the “ProductDetails” sheet, restrict the TASS sample to hedge funds that report net returns in USD at monthly frequency. Limit the observation period to 2005 to 2023. Remove backfilled returns using the “DateAddedToTASS” data field from the “ProductDetailsDateAdded” sheet.<sup>26</sup> For simplicity, restrict the “PeopleDetails” sheet to each fund’s first CP (data fields “PersonTypeID” and “Sequence” equal to 4 and 1, respectively).

**2. CP characteristics:**

In the “PeopleDetails” sheet, use the name prefixes and the *genderize.io* API to guess the gender of each CP. Remove entities and individuals with missing gender. Use Appendix 3.A.1 to identify MPs and non-MPs among the CPs.

**3. Fund variables:**

Calculate performance ranks as described in Section 3.2.4. Express AUM in USD million. Requiring at least USD 5 million in AUM, calculate fund flows over the following 12 months and then winsorize the flows at the 1st and 99th percentiles (*FLOW12*). Calculate fund age (*FAGE*) using the “PerfStartDate” data field, in years.

**4. Fund characteristics:**

Categorize the twelve TASS investment strategies into six styles (see Section 3.2.4). Recode the redemption frequency as the number of days between redemption dates (e.g., 30 for monthly, 90 for quarterly), and calculate the restriction period (*REST*) as the sum of redemption frequency and redemption notice period. Restrict the minimum investment amount (*MININV*) to the range USD 1 to USD 250 million. Using the “DomicileCountry” data field, add a variable *ONSHORE* indicating whether the fund is domiciled in the US. In the “ServiceProviderDetails” sheet, filter for entries where “CompanyType” is set to “Prime Broker”, then use the “CompanyName” field to retrieve the name of the prime broker. Create a variable *BROKER* to indicate whether the fund employs a blue-chip prime broker (see Footnote 12).

**5. Regression estimation:**

Observe all variables at 12-month intervals and estimate the linear regressions reported on the next page.

*R* scripts are available from the authors.

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<sup>26</sup>The results also appear when backfilled returns are retained.

The table below presents the results of multivariate linear regressions examining the impact of female contact persons (CPs) and marketing persons (MPs) on hedge fund flows. The sample, obtained following the instructions on the previous page, consists of observations at annual intervals from January 2005 to December 2023. The dependent variable is hedge fund flows over the following 12 months,  $FLOW12(t+12)$ . The independent variables of interest are  $FEMALE\_CP$ ,  $FEMALE\_MP$ , and  $MALE\_MP$ .  $FEMALE\_CP$  equals 1 if the fund's first-listed CP is female.  $FEMALE\_MP$  ( $MALE\_MP$ ) equals 1 if the first-listed CP is a female (male) MP. Other independent variables include  $RANK\_CA12$ ,  $RANK\_FH12$ , and  $RANK\_RET12$  (CAPM alpha, Fung and Hsieh (2004) alpha, and cumulative-return rank over the previous 12 months);  $\log(AUM)$  (AUM);  $BROKER$  (blue-chip prime broker);  $MFEE$  (management fee);  $IFEE$  (incentive fee);  $HWM$  (high-water mark);  $LOCKUP$  (lockup period);  $LEVERED$  (leverage indicator);  $FAGE$  (fund age);  $\log(REST)$  (restriction period);  $\log(MININV)$  (minimum investment);  $PCAP$  (personal-capital indicator); and  $ONSHORE$  (fund domicile). Standard errors are clustered by fund and year-month,  $t$ -statistics are shown in parentheses; and all regressions include fixed effects for style and year-month.

	Dependent variable: $FLOW12(t+12)$					
	(1)	(2)	(3)	(4) No FoHF	(5)	(6) No FoHF
$FEMALE\_CP$	0.030** (2.496)	0.027** (2.243)	0.030*** (2.727)	0.032** (2.383)		
$FEMALE\_MP$					0.075*** (3.163)	0.074** (2.602)
$MALE\_MP$					0.000 (0.030)	0.004 (0.184)
$RANK\_CA12$	0.314*** (16.339)			0.315*** (14.496)	0.375*** (11.956)	0.395*** (11.047)
$RANK\_FH12$		0.299*** (13.864)				
$RANK\_RET12$			0.344*** (18.575)			
$\log(AUM)$	-0.027*** (-7.913)	-0.028*** (-7.909)	-0.031*** (-9.051)	-0.031*** (-6.972)	-0.024*** (-4.960)	-0.029*** (-4.415)
$BROKER$	0.004 (0.445)	0.004 (0.387)	0.003 (0.348)	0.005 (0.413)	0.003 (0.170)	0.008 (0.400)
$MFEE$	-0.578 (-0.606)	-0.550 (-0.582)	1.664* (1.659)	1.263 (0.941)	-3.478* (-1.714)	-3.670 (-1.333)
$IFEE$	-0.118 (-1.279)	-0.098 (-1.062)	-0.146 (-1.265)	-0.006 (-0.040)	0.043 (0.234)	0.290 (1.156)
$HWM$	0.012 (0.899)	0.013 (1.005)	0.023 (1.342)	0.000 (0.008)	0.043* (1.888)	0.053* (1.788)
$LOCKUP$	-0.001 (-1.636)	-0.001* (-1.903)	-0.002** (-2.485)	-0.001 (-1.551)	-0.001 (-0.977)	-0.002 (-1.060)
$LEVERED$	0.009 (0.835)	0.008 (0.720)	0.010 (0.966)	0.017 (1.345)	-0.009 (-0.506)	0.001 (0.033)
$FAGE$	-0.002 (-1.521)	-0.002 (-1.445)	-0.006*** (-3.384)	-0.002 (-0.863)	-0.002 (-1.353)	-0.002 (-0.696)
$\log(REST)$	0.004 (0.456)	0.004 (0.481)	0.005 (0.516)	0.012 (1.099)	-0.002 (-0.155)	-0.007 (-0.359)
$\log(MININV)$	0.013*** (3.644)	0.013*** (3.726)	0.012*** (3.843)	0.014*** (3.336)	0.008 (1.421)	0.013 (1.574)
$PCAP$	0.009 (1.032)	0.007 (0.831)	0.005 (0.478)	0.000 (-0.049)	0.024 (1.383)	0.027 (1.201)
$ONSHORE$	0.007 (0.618)	0.004 (0.346)	0.001 (0.103)	-0.001 (-0.101)	-0.014 (-0.785)	-0.010 (-0.485)
FE (style, year-month)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,415	8,415	10,690	6,195	3,199	2,355
Adj. $R^2$	0.098	0.094	0.108	0.088	0.112	0.101
Within adj. $R^2$	0.057	0.053	0.058	0.058	0.073	0.075

