Delegated Leverage and Asset Prices: Evidence from the Hedge Fund Industry

Charles Cao[1], Grant Farnsworth[2], Hong Zhang[3], and Yijun Zhou[4]

We would like to thank Hui Chen, Yong Chen, Darrell Duffie, Paul Ehling, Thierry Foucault, René Garcia, Xavier Giroud, Bin Han, Pierre Hillion, Gerard Hoberg, Marcin Kacperczyk, Ron Kaniel, Bill Kracaw, Kai Li, Ye Li, Semyon Malamud, Pedro Matos, Roni Michaely, Christine Parlour, Adriano Rampini, Adam Reed, Lukas Schmid, Kelly Shue, Clemens Sialm, Tim Simin, Mathew Spiegel, Laura Starks, and seminar and conference participants of Penn State University, Singapore Management University, Tsinghua University, the 2023 Annual Hedge Fund Research Conference in Paris, and the 2024 China International Conference in Finance for invaluable comments.

[1] Smeal College of Business, Pennsylvania State University, University Park, PA, 16802, USA; E-mail: qxc2@psu.edu.
[2] Neeley School of Business, Texas Christian University, Fort Worth, TX, 76129; E-mail: g.v.farnsworth@tcu.edu.
[3] Lee Kong Chian School of Business, Singapore Management University, 50 Stamford Road, Singapore 178899; E-mail: hongzhang@smu.edu.sg.
[4] Baruch College, City University of New York, 55 Lexington Ave, New York 10010, USA; E-mail: yijun.zhou@baruch.cuny.edu

Delegated Leverage and Asset Prices: Evidence from the Hedge Fund Industry

Abstract

Contrary to the conventional wisdom that less constrained investors achieve superior returns, existing studies find little evidence that the use of leverage enhances hedge fund performance. To reconcile this puzzle, we extend the model of Berk and Green (2004) and empirically test its predictions including 1) Hedge funds reap leverage-based economic rents via fees; 2) Adverse conditions prompt funds to simultaneously reduce leverage and increase holding betas; and 3) A hedge fund leverage tightness factor predicts asset returns, especially during periods with reduced hedge fund leverage. Our results provide a leverage-based framework for hedge funds with important asset pricing implications.

Keywords: Hedge Funds; Leverage; Leverage Constraints, Delegated Portfolio Management; Asset Pricing

JEL Codes: G11; G12; G20

Leverage and borrowing constraints play a key role in the financial markets. Since the seminal work of Black (1972; 1993), researchers have recognized that borrowing restrictions affect investments and asset returns. More recently, Frazzini and Pedersen (2014) indicate that constrained investors tilt their portfolios toward high-beta assets, causing low-beta strategies to deliver abnormal returns. Boguth and Simutin (2018) consider mutual funds as a representative example of constrained investors and show that a leverage constraint factor constructed from their holding betas is priced in the cross-section of stock returns. Empirical evidence further shows that the leverage conditions of various financial intermediaries, such as broker-dealers, affect asset returns (Adrian, Etula, and Muir 2014; He, Kelly, and Manela 2017; Asness et al. 2020).

Despite the efforts in the literature to examine constrained investors and certain leveraged financial intermediaries, the impact of hedge funds, the quintessential levered investors, has received limited attention. This gap is surprising given the more substantial variation and impact of hedge fund leverage compared to those of other types of institutional investors, particularly during financial crises (e.g., the Long-Term Capital Management episode).[1] Even more puzzling, existing hedge fund studies find little evidence that leverage is related to superior performance (e.g., Agarwal and Naik 2004; Lo 2008; Liang and Qiu 2019), which challenges an important tenet of the literature: that less constrained investors should outperform their constrained counterparts.[2] This finding also raises doubts about why hedge funds employ leverage in the first place.

This paper aims to reconcile these apparent contradictions by examining the role of leverage in shaping the hedge fund industry and influencing asset returns through hedge fund policies. Our key intuition is that unconstrained investors may seek to exploit their leverage advantage through delegated portfolio management—referred to as *delegated leverage*—by setting up hedge funds and raising capital from investors who are unable to borrow. As we will detail shortly, this framework not only provides a leverage-based theory for hedge funds but also sheds light on the intricate relationship between hedge fund leverage, performance, and asset returns.

[1] See, among others, Banque de France (2007) for detailed discussions.
[2] Recent studies on leveraged buyout (LBO) funds, another important type of institutional investors using leverage, have also failed to observe a positive relationship between leverage and fund performance (see, e.g., Hüether, Schmid, and Steri 2022).

We formalize this intuition by extending Berk and Green's (2004) model to incorporate the asset pricing framework of Black (1972) and Frazzini and Pedersen (2014). In our model, a representative hedge fund raises capital from long-only investors who are unable to borrow. The hedge fund determines not only its fees, as in Berk and Green (2004), but also its leverage and portfolio betas based on the benefits and costs of leverage, which we will loosely refer to as *funding conditions*. In equilibrium, the tightness (i.e., the Lagrange multiplier) of hedge fund leverage constraints further influences expected asset returns.

Our model puts forth three novel predictions that can be empirically tested. First, if hedge fund leverage is an endogenous choice, higher leverage should lead to superior returns. However, in line with Berk and Green (2004), fund managers do not pass these benefits on to investors. Instead, they collect economic rents generated by leverage through fees, leading to a positive relationship between leverage and fees, but not necessarily between leverage and after-fee performance, which has been the focus of existing literature.

Secondly, our model predicts an important relationship between delegated leverage and investment policies. When facing adverse funding conditions, hedge funds will *simultaneously* reduce their leverage and shift their investments toward high-beta stocks. This prediction addresses a critical missing link in the literature: despite the theoretical prediction that more constrained investors should invest in higher beta stocks (e.g., Frazzini and Pedersen 2014; Boguth and Simutin 2018), there is a lack of investor-level evidence establishing a relationship between leverage and betas. Our model fills this gap by proposing a testable leverage-beta relationship.

Our final prediction relates to the asset pricing implications of delegated leverage. Intuitively, adverse funding shocks not only lead to reduced leverage and increased holding betas for hedge funds, but also tighten the leverage constraints of these funds. Hence, our model predicts a positive relationship between hedge fund holding betas and the tightness of constraints. Consequently, we can follow the literature to construct a tightness factor, using hedge fund holding betas, that predicts the cross-section of asset returns. A unique feature of the hedge fund tightness factor is that its pricing power is concentrated in periods of reduced hedge fund leverage.

To test these predictions, we use data provided by three databases (TASS, HFR, and BarclayHedge) to compile a list of hedge fund companies, which we also refer to as hedge fund "families." We then track the holdings of matched hedge fund companies, as reported in form 13F. While the hedge fund 13F filings allow us to infer holding betas, hedge funds do not disclose their leverage directly.[3] To address this issue, we propose a novel measure of leverage as 13F equity holdings scaled by assets under management (AUM), which we refer to as *asset-implied leverage*. Although this measure has limitations, such as the lack of information on short positions and derivatives, it aligns well with our model and the industry definition of leverage.[4] As the 13F holding information is available at the hedge fund company level, we construct this measure for each hedge fund company. It provides a reasonable estimation of relative leverage ranks and changes in leverage over time, after accounting for time-invariant characteristics and positions. Any remaining estimation noise would work against finding leverage-related effects.

We first use this measure to examine whether hedge funds with higher leverage collect more economic rents in the form of fees. Following the literature (Agarwal, Daniel, and Naik 2009; Jorion and Schwarz 2014; and Yin and Zhang 2023), we calculate before-fee for hedge funds, and we refer to the difference between the before-fee returns and after-fee returns (reported by hedge funds) as "dynamic fees."

At the beginning of each quarter, we sort hedge fund companies into quintiles based on their asset-implied leverage and track the dynamic fees for each quintile. We find an almost monotonically increasing pattern in dynamic fees. Consistent with our model's prediction, fund families in quintiles with higher leverage earn higher dynamic fees. For example, the top-quintile fund companies generate an average annual dynamic fee of 1.98%, which is approximately 42% higher than what the bottom-quintile fund companies collect. This fee spread is statistically and economically significant and is robust to risk adjustments using Fung and Hsieh's (2004) seven-

[3] Because of this issue, previous studies use estimated or static leverage ratios (e.g., Lo 2008) or proprietary data (e.g., Ang, Gorovyy, and van Inwegen 2011). These measures lack the power to test the asset pricing impact of the entire hedge fund industry.
[4] Practitioners such as prime broker-dealers and regulators often refer to (long) leverage as the long market position of hedge funds divided by their net equity (as discussed by Banque de France 2007; Ang, Gorovyy, and van Inwegen 2011, among others). Our measure captures the net equity part well, though the 13F holdings may miss some information about short and derivative positions. Nonetheless, it offers a reasonable and consistent measure of leverage for all hedge fund families.

factor model. Moreover, top-quintile fund companies exhibit a higher Sharpe Ratio without bearing more left-tail risk. They outperform the bottom-quintile companies as judged by the seven-factor adjusted before-fee returns, but not after-fee returns. Multivariate regression analyses further confirm the positive relationship between leverage and dynamic fees. These findings provide support for our model's prediction that hedge funds generate leverage-based economic rents and capture them through fees.

Next, we investigate how hedge funds adjust their leverage and investment policies in response to adverse funding conditions. To accomplish this, we focus on *active changes* in hedge fund leverage and holding beta, accounting for the influence of stock price movements. Poor fund returns reveal adverse investment and funding conditions, which may trigger margin call-type funding shocks. Our model, therefore, predicts that hedge funds will respond to poor returns by reducing leverage and simultaneously increasing holding beta. As a result, past fund returns should be positively associated with leverage changes and negatively associated with holding beta changes. Our empirical analysis confirms these relationships. Furthermore, we find evidence that these adjustments occur simultaneously and in opposite directions. Panel regression analysis indicates that a 1% reduction in past performance increases the likelihood of simultaneous and opposite leverage-beta adjustments by approximately 0.33%.[5]

Thus far, our empirical results confirm the model's predictions on hedge fund policies. Given that hedge fund characteristics may also influence investment and leverage policies, we next examine their impact on fund policies. Two important observations emerge. First, we find that the relations predicted by our model are stronger for single-fund companies than for multiple-fund companies. This finding is reasonable because multiple-fund companies may face coordination issues across their affiliated funds and have the flexibility to adopt more complex leverage strategies that may not be fully captured by our leverage measure.

Second, investor flows do not seem to be related to fee policies or the simultaneous active adjustments of leverage and holding betas, suggesting that investors play a lesser role in

[5] In contrast, past returns have no relationship with the simultaneous same-direction change in leverage and holding betas. This placebo test suggests that our analysis has the right power to detect simultaneous fund policy adjustments.

determining fund policies than managers do.[6] This lack of influence contrasts with the mutual fund industry. Hitzemann, Sokolinski, and Tai (2022) documented that mutual fund investors' demand for leverage strongly impacts fund fee policies. Their findings offer an alternative, investor-driven mechanism to explain fund policies. To further investigate this alternative mechanism, we gather information on hedge fund investors from Preqin and examine how their leverage preferences affect hedge fund policies. We observe a very limited impact, confirming that leverage and fee policies remain primarily under the control of hedge fund managers, consistent with our model.[7]

Finally, we delve into the asset pricing implications of delegated leverage. We adopt the approach of Boguth and Simutin (2018) to construct a *delegated leverage constraint tightness* (*DLCT*) factor based on hedge fund holding betas. Since the leverage of single-fund companies is measured with less noise, we aggregate the holding betas of these families as our primary empirical proxy. Our *DLCT* factor cannot be explained by traditional or supply-side funding factors, such as the LIBOR rate or the intermediary capital risk factor of He, Kelly, and Manela 2017, suggesting that it captures a novel source of risk. Indeed, when we sort stocks into quintiles based on their exposure to the factor, the top and bottom quintile stocks exhibit a significant and economically sizeable return spread of 0.58% per month (or 7.2% per year). The results remain significant when using risk-adjusted returns from the Fama-French-Carhart four-factor model and the Pastor-Stambaugh liquidity-enhanced five-factor model.

To formally assess the pricing power of the *DLCT* factor, we conduct Fama-MacBeth regressions and control for a large set of factors known to affect asset returns. Across all specifications, higher exposure to the hedge fund *DLCT* factor predicts significantly lower returns. The economic magnitude is substantial: a one-standard-deviation increase in factor exposure corresponds to a 0.19% reduction in monthly return (2.27% per year).

Furthermore, as predicted in our model, the pricing power of the hedge fund *DLCT* factor is concentrated in periods when hedge funds tighten their leverage, suggesting that the pricing power

[6] This observation can be explained by investors chasing past returns, which allows returns to absorb the effect of flows.
[7] In other words, our results are consistent with a competitive supply of investor capital regardless of their leverage preferences. This property is similar to the original assumption of Berk and Green (2004) that is adopted by our model. We thank Darrell Duffie for suggesting this test on hedge fund investors (i.e., limited partners) to differentiate alternative models.

of the *DLCT* factor is driven by hedge fund leverage constraints. Additional robustness tests show that the exclusion of penny stocks and the inclusion of exposure to the mutual fund leverage constraint tightness (LCT) factor do not change our results.

More broadly, hedge funds may affect asset prices through two channels in our model. First, the tightness of hedge fund leverage constraints, if priced, affects expected asset returns by flattening the security market line (as shown in Black 1972 and Frazzini and Pedersen 2014). This channel is investigated and supported by the aforementioned DLCT tests. Second, disruptions in hedge fund capital may also alter the exposure of hedge fund-invested stocks to the hedge fund *DLCT* factor. While the microfoundation of risk exposure is not the primary focus of the literature (or our paper), we nonetheless provide an in-depth event study on Lehman Brothers' bankruptcy, which can offer insights into how hedge funds differ from other institutions through this second channel. The bankruptcy triggered a liquidity crunch among funds that relied on Lehman as a prime broker (Aragon and Strahan 2012). We observe that greater holdings by Lehman-connected hedge funds significantly increased stocks' exposure to the hedge fund *DLCT* factor immediately after bankruptcy. In contrast, mutual fund holdings and other non-hedge fund institutional holdings partially offset this effect. Collectively, the Lehman event identifies a unique role that hedge funds play in affecting assets during a period of substantial funding shocks.

This study contributes to asset pricing literature in several ways. To our knowledge, we are the first to examine the impact of leverage on both delegated portfolio management and asset prices. Existing asset pricing studies often treat the frictions of delegated management, such as leverage constraints, as exogenous. However, the equilibrium conditions in the securities market and delegated portfolio management affect each other and should be jointly determined (Gârleanu and Pedersen 2018). Our analysis applies this insight to leverage. By extending Berk and Green's (2004) model to the asset pricing framework of Black (1972) and Frazzini and Pedersen (2014), we demonstrate that certain investors launch hedge funds to exploit their leverage advantage. Our model provides the first leverage-based framework for hedge funds, which also sheds light on the effect of delegated leverage on asset prices.

We also contribute to the literature on the economic underpinnings of hedge funds.[8] Agarwal and Naik (2004) point out that some hedge fund strategies resemble those of a short put option on the market index. Jylha and Suominen (2011) show that hedge funds arise endogenously to mitigate market segmentation. We introduce hedge fund leverage into the economics of the hedge fund industry and explain several puzzling results about hedge fund leverage.

Our study also contributes to the literature on the impact of leverage on asset pricing. Prior research focuses on two types of agents: leveraged financial intermediaries and constrained investors. For instance, He and Krishnamurthy (2012; 2013) suggest that the borrowing limits of financial intermediaries affect asset prices.[9] On the investor side, Boguth and Simutin (2018) and Hitzemann, Sokolinski, and Tai (2022) extend the framework of Frazzini and Pedersen (2014) to propose a mutual fund-based LCT factor and a positive beta-fee relationship for high beta mutual funds.[10] Our approach extends Berk and Green (2004) to examine delegated leverage and proposes a new measure of portfolio-level leverage. This measure is crucial for leverage-related studies but is difficult to observe for other types of investors.

This paper is structured as follows: Section I presents the model of delegated leverage and its testable hypotheses. Section II describes the data used in our analysis. Section III examines the role of leverage in delegated portfolio management. Section IV investigates the asset pricing implications of the hedge fund factor. Section V explores alternative explanations for our findings. Section VI provides concluding remarks.

---

[8] In the literature, Brunnermeier and Nagel (2004), Banque de France (2007), Lo (2008), and Ang, Gorovyy, and van Inwegen (2011) show that hedge funds move capital and change leverage around financial crises. Brown et al. (2008, 2009) examine how operational risk affects hedge fund leverage. Teo (2011) explores whether leveraged speculators such as hedge funds are vulnerable to a margin spiral, as specified in Brunnermeier and Pedersen (2009). Lan, Wang, and Yang (2013) examine the fee structure, which impacts fund leverage. Barth, Hammond, and Monin (2020) report a weak relationship between hedge fund leverage and portfolio risk and a strong influence of the market beta on leverage. Agarwal (2021) provides a theoretical model in which hedge fund leverage is determined by moral hazard and liquidity insurance. Aragon, Ergun, and Girardi (2022) document that hedge funds with better investment opportunities utilize lower liquidity buffers (such as cash).

[9] For instance, He, Kelly, and Manela (2017) document the empirical pricing power of the equity capital ratio of primary dealers. Adrian, Etula, and Muir (2014) and Asness et al. (2020) show that the leverage and margin debt of broker-dealers proxy for the stochastic discount factor..

[10] Several studies also estimate the shadow cost of capital from passive leveraged funds (e.g., Frazzini and Pedersen 2022 and Lu and Qin 2021) and the shadow cost of capital for market participants (e.g., Koijen and Yogo 2016; Kisin and Manela 2016; Fleckenstein and Longstaff 2020). Given that hedge funds are the leading leveraged investors in the market, our results are consistent with Jylha's (2018) finding that regulatory changes in margin requests, which shift the costs of leverage users, affect the slope of the security market line.

I. Theoretical Framework

This section presents a framework to examine delegated leverage and its implications for asset pricing. Our model is built upon the work of Berk and Green (2004; hereafter BG) and leverage-constrained asset pricing frameworks (e.g., Black 1972; Frazzini and Pedersen 2014, hereafter FP).

A. Assumptions on Securities and Investors

Consider a two-period economy with one risk-free asset and N risky assets. The risk-free asset pays a second-period gross return R_f, while risky assets pay *excess* returns $\boldsymbol{R_e}$ in the second period. In other words, $\boldsymbol{R_e} = \boldsymbol{R} - R_f\mathbb{1}$, where $\boldsymbol{R}$ refers to the $N \times 1$ vector of risky asset returns, $\mathbb{1}$ is the vector of ones with N elements, and R_f is the risk-free rate. Denote the covariance matrix of the N assets by $\boldsymbol{\Sigma}$ (an $N \times N$ matrix). Further assume that risky assets are in positive net supply, while the supply of the risk-free asset is elastic. In this framework, a continuum of investors holds a total amount of endowed capital, W, which they can invest in the first period. To focus on the role of leverage, we assume that all investors have the same quadratic utility function with risk aversion γ. While investors cannot take leverage on their own, they can delegate their investment to a hedge fund that has the ability to take leverage by borrowing using the risk-free asset. The hedge fund does not have endowed capital. Hence, to benefit from its leverage advantage, the hedge fund (h) raises capital, denoted as W_h, from investors in the first period. It invests this capital (potentially leveraged) in the risky assets in the second period. A representative long-only investor (l) then invests the remaining capital, $W_l = W - W_h$, in risky assets. By the end of the second period, asset returns are realized. The hedge fund manager needs to decide how to share leverage-generated economic rents with investors—an issue we will visit later.

We denote the investment policies of the hedge fund and the representative long-only investor as $\boldsymbol{\theta}_k$ ($k \in \{h, l\}$), a $N \times 1$ vector with its n^{th} element denoting the investment weight of the respective investor in the n^{th} risky asset. The fraction and total amount of wealth invested in risky assets are $\theta_k^R = \mathbb{1}'\boldsymbol{\theta}_k$ and $W_k^R = \theta_k^R W_k$, respectively. Investors are subject to heterogeneous borrowing constraints:

$$\mathbb{1}'\boldsymbol{\theta}_k = \theta_k^R \leq m_k,\ k \in \{h, l\} \tag{1}$$

where m_k denotes the maximum leverage ratio, with $m_l = 1$ for the long-only investor and $m_h > 1$ to be endogenously determined for the hedge fund.

We further assume that the hedge fund manager invests according to the risk aversion of fund investors, precluding moral hazard effects in our model. This assumption allows us to focus on the role of leverage. Hence, investor k ($k \in \{h, l\}$) makes first-period investment decisions by maximizing the following expected utility function:

$$U_k = \mathbb{E}\left[\boldsymbol{\theta}_k'\boldsymbol{R}_e + R_f\right] - \frac{\gamma}{2}\boldsymbol{\theta}_k'\boldsymbol{\Sigma}\boldsymbol{\theta}_k, \tag{2}$$

To achieve equilibrium, the economy needs to satisfy two conditions. First, the security market clears, following the FP model:

$$\sum_{k\in\{h,l\}} W_k\boldsymbol{\theta}_k = W^R\boldsymbol{X}^R, \tag{3}$$

where W^R is the total amount of wealth that all investors invest in risky assets, and $\boldsymbol{X}^R$ is the vector of market portfolio weights of all risky assets (i.e., $\mathbb{1}'\boldsymbol{X}^R = 1$). Note that W^R is not equal to the total wealth that investors initially had, due to the presence of hedge fund leverage.[11]

Second, as in the BG model, the market for delegated portfolio management equilibrates. Specifically, the hedge fund manager, based on her investment policy, determines the optimal fee and leverage policies to attract the desired amount of capital W_h. Hence, we extend the BG model to include leverage and a quadratic cost function of leverage. The hedge fund manager solves the following problem:

$$Max_{f,m_h} \quad f \times W_h, \tag{4}$$

where f is the management fee as a percentage of the capital raised. Since fund investors have the option to withdraw capital and invest it with the long-only investor, the fund needs to deliver the expected return of the long-only investor, $\bar{r}_l$, to its investors, and then split any additional economic

[11] From Eq. (3), we have $W^R = \theta_l^R W_l + \theta_h^R W_h$, whereas the total wealth is $W = W_l + W_h$.

rents between the fund manager and investors. In a market with competitive capital supply, the fund delivers the following per-dollar returns to investors (in addition to $\bar{r}_l$):

$$\delta_h - f - bW_h - \frac{1}{2}cm_h^2 = 0. \tag{5}$$

In Eq. (5), the variable δ_h refers to the economic rents that the fund can generate due to its leverage advantage. Specifically, $\delta_h = \mathbb{E}[\boldsymbol{\theta}_h'\boldsymbol{R}_e] - \mathbb{E}[\boldsymbol{\theta}_l'\boldsymbol{R}_e] \equiv \bar{r}_h - \bar{r}_l$, where $\bar{r}_h$ and $\bar{r}_l$ refer to the expected returns of the hedge fund and the long-only investor.[12] Next, b is operational costs due to diseconomies of scale, as described in Berk and van Binsbergen (2015, 2017). Finally, c denotes the cost of taking leverage, which may include borrowing fees, collateral requests, and other restrictions that fund brokers may impose.

Economically speaking, δ_h is the leverage-derived excess performance delivered by the hedge fund over the returns of the long-only investor, after accounting for fees and costs. When fund investors are unable to leverage their investments individually and compete to supply capital to the market, they receive long-only returns, while the hedge fund manager retains the economic rents generated through leverage. This equilibrium condition allows the market for delegated portfolio management to stabilize via fund size.

Our model extends the BG model to establish delegated portfolio management and generalizes their model in two important ways. First, BG does not model the source of successful managers' abilities. We explicitly consider leverage as a tool that enables hedge fund managers to generate economic rents. This allows us to examine how leverage affects the distribution of economic rents between the manager and investors. Second, the BG model assumes that managers' actions do not affect the prices of the underlying assets. We allow managerial decisions to affect asset prices.

[12] The variable δ_h is equivalent to the expected excess return that fund managers can generate, which reflects managerial skills in BG's original model (i.e., ϕ_t in their notation, where the expectation is based on all observable information). The excess return in BG is defined as benchmark-adjusted (because mutual fund managers track benchmarks). We instead focus on the return difference between the hedge fund manager and long-only investors. Conceptually, the return of the long-only investors can be regarded as a natural benchmark in our setup.

Overall, our model introduces a mechanism through which successful managers' abilities, including their skill in utilizing leverage, affect asset prices.[13]

B. Asset Prices and Fund Policies in Equilibrium

We now describe the equilibrium asset prices and fund policies. In the equilibrium, investors maximize their utility functions as defined in Eq. (2), subject to their leverage constraints of Eq. (1) and the security market-clearing condition of Eq. (3). In addition, the hedge fund manager solves the optimization problem of Eq. (4), subject to the sharing rule of Eq. (5). The following lemma describes the asset prices of the economy.

Lemma 1: Assume that investors make optimal investment decisions subject to leverage constraints. The equilibrium asset returns satisfy:

$$\mathbb{E}[\boldsymbol{R}_e] = \boldsymbol{\beta}(\mathbb{E}[R_{mkt}] - \psi) + \psi\mathbb{1}, \quad (6)$$

where R_{mkt} is the excess return of the market portfolio, $\boldsymbol{\beta} = cov(\boldsymbol{R}_e, R_{MKT})/var(R_{MKT})$ is the vector of asset covariance with the market scaled by the variance of market returns, and ψ is the average Lagrange multiplier, measuring the market-wide tightness of leverage constraint. Mathematically, $\psi = \sum_k \left(\frac{W_k}{\mathrm{W}}\right)\phi_k$, where ϕ_k $(k \in \{h, l\})$ refers to the Lagrange multiplier faced by each type of investor.[14]

Our Online Appendix provides the proof of Lemma 1 and subsequent propositions. Lemma 1 establishes a leverage-enhanced CAPM model, which has been widely explored in the literature (e.g., FP). The main idea behind this asset pricing framework is that the borrowing constraints of investors impact the cross-section of expected asset returns through ψ; as a result, the value of ψ

[13] Gârleanu and Pedersen (2018) examines how (in)efficiency of asset management industry affects the securities market by introducing mutual fund search frictions into the Grossman-Stiglitz's (1980) model. We differ by focusing on the BG framework, which allows us to explicitly model leverage originated in the asset management industry. Future research can surely examine or incorporate other types of managerial abilities (e.g., on information processing).
[14] In other words, the i-th asset satisfy $\mathbb{E}[r_i] = \beta_i(\mathbb{E}[R_{mkt}] - \psi) + \psi$. When we allow for heterogeneity in risk aversion, Eq. (6) still holds with $\psi = \frac{\bar{\gamma}}{\mathrm{W}}\sum_k \left(\frac{W_k\phi_k}{\gamma_k}\right)$, where $\frac{1}{\bar{\gamma}} = \frac{1}{W}\sum_k \frac{W_k}{\gamma_k}$.

reflects the tightness of leverage constraints. The novelty of the economy described in this model centers on the presence of delegated leverage and the hedge fund. We summarize the fund's policies in the following proposition.

Proposition 1: Assume that the hedge fund manager maximizes her economic rents and investors supply their capital competitively in the market.

1) When the leverage constraint of the long-only investor is strictly binding (i.e., $\theta_l^R = 1$), the hedge fund outperforms the long-only investor. Moreover, the hedge fund's outperformance increases with the leverage it takes. Denoting hedge fund leverage as m_h and the marginal benefit of leverage as $\rho = \frac{\mathbb{1}'\boldsymbol{\Sigma}^{-1}\boldsymbol{R}_e}{\mathbb{1}'\boldsymbol{\Sigma}^{-1}\mathbb{1}}$, which is determined by the investment opportunity of risky assets, the hedge fund's outperformance is given by:

$$\delta_h = \bar{r}_h - \bar{r}_l = \rho \times (m_h - 1). \tag{7}$$

2) When $0 < \frac{1}{2b}\left(\frac{\rho^2}{2c} - \rho\right) < W$, the fund adopts the following optimal policies:[15]

$$m_h^* = \frac{\rho}{c};\ f^* = \frac{1}{2}\left(\frac{\rho^2}{2c} - \rho\right), \tag{8}$$

Note that optimal hedge fund leverage increases with the marginal benefit of leverage (ρ) and decreases with the cost of leverage.

Proposition 1 focuses on the case when the leverage constraint of the long-only investor is binding, allowing the hedge fund to retain all economic rents. It offers essential insights into our model's economy. First, a leverage advantage can be transformed into performance. This property restores the conventional wisdom that less constrained investors should make superior investments. In our setup, the strict binding of the long-only investor's leverage constraint restricts the potential

[15] This restriction prevents the corner solution in which the marginal benefit of leverage is so enormous that the hedge fund wants to raise more capital than what investors can supply.

returns the investor can attain. In contrast, the flexibility of taking leverage allows the hedge fund manager to outperform leverage-constrained investors.[16]

Secondly, aligning with the rationale presented by BG, when investors competitively supply capital to the delegated portfolio management market, the economic rents generated by leverage primarily accrue to the hedge fund manager. In other words, the hedge fund serves as a means for the manager to capitalize on her leverage advantage.[17] This property reconciles the importance of leverage and the insignificant relationship between leverage and the after-fee performance that investors receive (e.g., Agarwal and Naik 2004; Liang and Qiu 2019).

Finally, the hedge fund benefits from higher leverage when the underlining securities market provides better investment opportunities for investors with a leverage advantage—favorable marginal benefit of leverage-based investment and lower borrowing costs. In our model, the marginal benefit is captured by the parameter $\rho = \frac{\mathbb{1}'\boldsymbol{\Sigma}^{-1}\boldsymbol{R_e}}{\mathbb{1}'\boldsymbol{\Sigma}^{-1}\mathbb{1}}$; a higher value reflects a greater investment advantage enjoyed by the hedge fund, when compared to that of the long-only investor. In contrast, higher leverage costs imposed by the securities lending market or fund brokers reduces optimal leverage. We can interpret the marginal benefit and cost (of leverage-based investment) as funding-condition state variables, which allow us to examine how asset prices and hedge fund leverage vary across different states.

Overall, Proposition 1 provides the rationale for the emergence of delegated leverage and hedge funds in the economy. It also lays out the groundwork for us to understand two important implications of delegated leverage. First, in the existing literature, the asset pricing implications of Proposition 1 are tested using security betas or investors' holding betas, but there is a lack of direct evidence regarding the relationship between investors' beta choices and leverage. Our framework of delegated leverage bridges this gap. Second, if hedge funds serve as the marginal investor in the economy, it is expected that asset returns would be influenced by the tightness of delegated

[16] Since our economy consists of only two investors, the market return is their weighted average return. Hence, the hedge fund outperforms the market, whereas the long-only investor underperforms.
[17] When the market exhibits friction in capital flows (see, e.g., Cao, Farnsworth, and Zhang 2021), the hedge fund manager may have incentives to share the economic rents.

leverage constraints. Our model addresses these issues by establishing a direct link between hedge fund leverage, its holding beta, and the tightness of delegated leverage constraints.

In our model, $\beta_h = \boldsymbol{\beta}'\boldsymbol{\theta}_h$ and $\bar{\beta}_h = \boldsymbol{\beta}'\boldsymbol{\theta}_h / m_h$ denote the levered and leverage-adjusted betas of the hedge fund holdings, respectively. Between the two holding betas, the latter better reflects the tilting of the holding portfolio toward high beta stocks.[18] To simplify notation, we refer to the leverage-adjusted holding beta as "*hedge fund holding beta*" or simply "*hedge fund beta*" when there is no confusion. The following proposition describes the relationship between hedge fund leverage, hedge fund holding beta, and the priced tightness of delegated leverage constraints.

Proposition 2: An adverse shock in funding conditions (i.e., a declining marginal benefit of leverage, ρ, or a hiking funding cost, c) gives rise to the following three consequences:

1) Tightened hedge fund leverage (i.e., smaller m_h).
2) Increased hedge fund holding beta (i.e., higher $\bar{\beta}_h$).
3) Greater tightness of delegated leverage constraints (i.e., higher ϕ_h).

Proposition 2 clarifies the interplay between hedge fund leverage policies, hedge fund investment policies (reflected in their holding betas), and the price impact of delegated leverage stemming from the priced tightness of delegated leverage constraints. As funding conditions vary, the first two outcomes of the proposition indicate a negative relationship between hedge fund leverage and its holding beta. This leads to a testable prediction regarding the relationship between investors' investment and leverage policies. The second and third outcomes confirm that beta-based factors (e.g., Frazzini and Pedersen 2014; Boguth and Simutin 2018) predict the cross-section of asset returns in the context of delegated leverage. Hence, we will follow the literature to explore the asset pricing power of hedge fund beta-based factors. The difference between our

[18] To see the intuition, consider two risky assets with betas 1.5 and 0.5. Now, compare the following two portfolios: $\boldsymbol{\theta_l} = (0.5, 0.5)'$ and $\boldsymbol{\theta_h} = (1, 1)'$. The first (un-levered) portfolio has a portfolio beta of 1. The second has a levered portfolio beta of 2. However, the second portfolio does not invest more into the high-beta stock because its leverage-adjusted portfolio beta (by $m_h = 2$) is still 1. In contrast, a third portfolio of $\boldsymbol{\theta}'_{\boldsymbol{h}} = (1.5, 0.5)'$ has a higher leverage-adjusted portfolio beta—this portfolio tilts more toward high-beta stocks in its holdings than the previous two portfolios.

factor and existing factors arises from the special role hedge fund leverage plays in determining asset prices and the extra restriction introduced by the first prediction.

C. Development of Testable Hypotheses

We now highlight a few properties of our model that guide our empirical analysis. The first implication of the model is that leverage enables hedge funds to outperform leverage-constrained investors. However, the resulting economic rents are earned by fund managers via fees, as predicted by Proposition 1. We summarize this implication in the following hypothesis.

Hypothesis 1: Higher leverage allows hedge funds to achieve superior before-fee performance and collect more fees.

Testing the above hypothesis poses an empirical challenge since hedge funds do not disclose their leverage. Our model suggests an empirical proxy to address this issue. Specifically, we can use the equity holding of a fund scaled by its AUM (which is essentially m_h in our model) as a proxy for its leverage. Although our model assumes that hedge funds only invest in stocks and use the risk-free asset to borrow capital, in practice, funds may use derivatives and other borrowing methods to build up leverage. Nonetheless, this measure provides a first-order proxy to link our model to real data.

Next, we move to the beta-leverage relationship as predicted in Proposition 2. In our model, hedge fund leverage depends on leverage-related investment benefits (ρ) and borrowing costs (c). While these parameters are not directly observable, we can use realized hedge fund returns to infer their combined impact. Since successful hedge funds persistently deliver superior performance, a negative return signifies a deteriorating investment opportunity, an increased cost, or a combination of both. In such cases, we anticipate that the hedge fund will reduce its leverage after experiencing poor performance. Proposition 2 further suggests that the hedge fund will adjust its holdings toward high-beta stocks when reducing leverage, leading to simultaneous adjustments in leverage and investment policies. These contemporaneous changes in leverage and beta lead to the following hypothesis.

Hypothesis 2: An adverse shock in funding conditions, as revealed by poor fund performance, induces hedge funds to reduce leverage and increase holding beta *simultaneously*.

The recent literature utilizes securities betas and holding betas to formulate asset pricing factors that reveal the tightness of leverage constraints. Examples include FP's betting-against-beta (BAB) factor and Boguth and Simutin's (2018) mutual fund leverage constraint tightness (LCT) factor. Proposition 2 suggests that hedge fund betas can likewise serve as a basis for creating factors.

Note that the hedge fund tightness factor provides two research benefits. First, the holding betas of long-only investors lack variation when their leverage constraints are binding. In contrast, hedge fund policies have the potential to convey more information about funding conditions as they vary across different states. Secondly, the first property of Proposition 2 enhances the power of our tests. Specifically, the influence of the hedge fund beta factor on asset prices, if originating from leverage constraints, should be concentrated in periods when hedge funds tighten their leverage. Should the data validate this additional prediction, it would provide evidence to support the argument that delegated leverage is the economic rationale underpinning the pricing power of the hedge fund beta factor. The above discussion leads to the following hypotheses:

Hypothesis 3A: Hedge fund holding beta factor is a priced factor that can explain asset returns.

Hypothesis 3B: The pricing power of the hedge fund beta factor increases in states with tighter hedge fund leverage.

II. Data and Construction of the Variables

A. Data Sources

For our empirical tests, we gather data from various databases. First, we obtain hedge fund holding information from 13F filings reported to the Securities and Exchange Commission (SEC). Since 1978, institutional investors managing at least one hundred million U.S. dollars have been required to file 13F forms with the SEC each quarter. These filings provide details for U.S. equity holdings of more than $200,000 dollars or more than 10,000 shares.

To identify hedge fund management companies, we utilize multiple hedge fund databases following the approach of Brunnermeier and Nagel (2004) and Griffin and Xu (2009). We compile a master list of hedge fund company names by combining data from the TASS, HFR, and BarclayHedge databases, and then match this list with the names of institutions listed in Thomson Reuters Institutional Holdings (13F) to identify hedge fund companies. Subsequently, we manually review the SEC ADV forms of the matched institutions and require an institution to have more than 50 percent of its investments listed as “other pooled investment vehicles”, or more than 50 percent of its clients listed as “high net worth individuals” for inclusion in our hedge fund sample. Finally, we check the websites of each institution that satisfies the above requirements to ensure its primary business is related to hedge funds. Through this process, we identify around 1100 hedge fund management companies, which we refer to as hedge fund companies or families in our analysis.

Our sample of stocks contains common stocks for which we have accounting and stock market information from CRSP and Compustat databases. We exclude American Depository Receipts (ADRs) and stocks with incomplete information. The sample period of this study spans from 1994 to 2019.

B. Main Variables

Our main variables are constructed as follows. The asset-implied leverage ($L_{i,t}$) of hedge fund company *i* in quarter *t* is its aggregate holding assets divided by its aggregate AUM in quarter *t*.

$$L_{i,t} = \frac{Assets_{i,t}}{AUM_{i,t}} = \frac{\sum_s holding\ value_{i,s,t}}{AUM_{i,t}}, \tag{9}$$

where $holding\ value_{i,s,t}$ refers to the value of shares held by hedge fund company *i* in stock *s* in quarter *t*. Ang, Gorovyy, and van Inwegen (2011) report that equity leverage as implied by the information collected from prime brokers and derivatives exchanges is typically below 20. We therefore cap asset-implied leverage at the level of 20 (our results are robust to the use of alternative caps or no thresholds).

To identify leverage changes that reflect the active portfolio investment or discretionary decisions of the hedge fund company, we further construct a measure of *Active Leverage Change* as follows:

$$\Delta L_{i.t} = (L_{i,t} - \bar{L}_{i,t})/L_{i,t-1}, \tag{10}$$

where $\bar{L}_{i,t}$ is the counterfactual leverage, $\bar{L}_{i,t} = \frac{\sum_s holding\ value_{i,s,t-1} \times (1+stock\ return_{s,t})}{AUM_{i,t-1}}$, which measures the stock price-induced leverage variations when the hedge fund company sits on its portfolio without trading. By netting out this counterfactual influence, our measure captures the changes in leverage due to active portfolio adjustments made by the hedge fund company.

The holding beta ($HB_{i,t}$) of each hedge fund company i in quarter t is defined as the holding-value weighted-average stock beta of its portfolio, which is calculated as follows:

$$HB_{i,t} = \sum_s \frac{holding\ value_{i,s,t}}{\sum_s holding\ value_{i,s,t}} \times stock\ beta_{s,t}. \tag{11}$$

Again, to identify the holding beta change that results from the active action or discretionary investment decision of the hedge fund company, we construct a measure of *Active Holding Beta Change* as:

$$\Delta \mathrm{HB}_{i,t} = HB_{i,t} - \overline{HB}_{i,t}, \tag{12}$$

where $\overline{HB}_{i,t} = \sum_s \frac{holding\ value_{i,s,t-1} \times (1+stock\ return_{s,t})}{\sum_s holding\ value_{i,s,t-1} \times (1+stock\ return_{s,t})} \times stock\ beta_{s,t-1}$ is the counterfactual holding beta that reflects the effect of stock price changes without trading.

Next, we construct proxies using the before-fee returns of hedge funds to capture the economic rents reaped by fund managers. Since hedge fund returns provided by various databases are reported after-fees (net), we follow the method proposed in the literature (e.g., Agarwal, Daniel and Naik 2009; Jorion and Schwarz 2014; and Yin and Zhang 2023) to estimate the before-fee returns. The method considers investors' assets as call options on the fund's assets, where the strike prices are determined by the high watermark and hurdle provisions of the fund, as well as the timing of each investor's entry into the fund. We track the value and strike price of each investor over time and equate the percentage change in the fund's after-fee market value each month to the fund's after-fee realized returns. We solve, numerically, for the before-fee returns of each fund in each month. The difference between the before-fee and after-fee returns is the dynamic fee collected by the hedge fund. Since the asset-implied leverage is estimated at the hedge fund company level, we aggregate the before-fee returns, after-fee returns, and dynamic fees of each fund at the hedge fund company level.

We also construct a set of control variables to capture hedge fund company characteristics. These variables include the number of funds in the hedge fund company, the number of stocks held by the hedge fund company, and the fund flows received by the family. The last variable is calculated as dollar flows normalized by the lagged AUM multiplied by $(1 + r_{i,t})$, where $r_{i,t}$ is the return for funds managed by hedge fund company i in quarter t:

$$HF\ flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + r_{i,t})}{AUM_{i,t-1} \times (1 + r_{i,t})}, \tag{13}$$

In addition to fund family characteristics, we also construct a list of stock characteristics following the literature, including *Market equity*, *Book-to-market*, *Profits-to-assets*, *Asset growth*, *Stock return run up*, *Reversals*, and *Idiosyncratic volatility*.

Table 1 reports the descriptive statistics of the variables mentioned above at the hedge fund company-quarter panel level. The average value of 13F-reported holding assets in logarithm is \$19.93 billion, while the average of logarithmic AUM is \$19.82 billion. The self-reported after-fee return aggregated at the company level averages 1.39% per quarter, with a standard deviation of 7.36%, and exhibits moderate right skewness. The standard deviation and skewness of the before-fee returns are similar to those of the after-fee returns. In comparison, the average before-fee return is 1.73% per quarter. The dynamic fees average 0.35% per quarter. On average, each family manages 5 funds and holds 229 stocks.

Table 1 also presents summary statistics of asset-implied leverage, with a mean of 3.44 times, a median of 1.22 times, and a standard deviation of 5.10.[19] There is substantial variation in asset-implied leverage across hedge fund companies, ranging from 0.50 (the 25th percentile) to 3.72 (the 75th percentile). The holding beta averages 1.13 with a median of 1.06 and a standard deviation of 0.61. In the cross-section of hedge fund companies, the variation in holding beta ranges from 0.89 (the 25th percentile) to 1.31 (the 75th percentile). In the next section, we empirically test the effect of delegated leverage on the performance of hedge funds.

III. Hedge Fund Company-Level Evidence

We conduct portfolio and regression analysis to examine the extent to which hedge funds retain economic rents from leverage. In addition, we investigate whether hedge funds simultaneously change their leverage and holding beta policies when facing adverse funding conditions.

A. The Economic Rents of Leverage

We start by analyzing leverage through the lens of portfolio analysis. At the beginning of each quarter, we sort hedge fund companies into five quintiles based on their asset-implied leverage levels during the preceding quarter. Next, we aggregate the equal-weighted average of returns and

[19] Note that the average leverage does not equal to the average value of assets reported in the 13F scaled by the average AUM due to Jensen's Inequality.

dynamic fees generated by hedge fund companies within each quintile each month. We also use the Fama and French (1993) three factors, the Carhart (1997) four factors, the Pastor-Stambaugh (2003) five factors, and the Fung and Hsieh (2004) seven factors to obtain risk-adjust performance and dynamic fees for the sorted portfolios. To conserve space, we report results based on the Fung and Hsieh (2004) seven-factor model, though alternative models yield consistent risk-adjusted returns.

Panel A of Table 2 tabulates the average value of several characteristics of the sorted portfolios, including asset-implied leverage, log-assets, log-AUM, Sharpe Ratio, and skewness (obtained by using before-fee returns) within each sorted portfolio. Hedge fund companies exhibit significant variation in asset implied leverage, ranging from 0.18 in the lowest quintile to 10.36 in the top quintile. The first number (0.18) suggests that the bottom-quintile families do not invest their entire AUM in stocks, whereas the second number (10.36) implies that, for each dollar received from investors, families in the top-quintile borrow an additional $9.36 to invest in stocks. The difference between the top and bottom quintiles of families suggests that our asset-implied leverage captures important variations across hedge fund investment policies.

The AUM of hedge fund companies decreases over the leverage quintiles, suggesting that leverage may serve as a substitute for investors' capital. To ensure that the impact of leverage is not solely explained by fund size effects, such as diseconomies of scale, we include company fixed effects and total assets as control variables in subsequent regression analyses. Furthermore, fund companies with high leverage also exhibit higher Sharpe Ratios, suggesting that fund managers use leverage to generate economic rents.

One potential concern is that these high Sharp Ratio funds may load on downside risk to manipulate Sharpe Ratios (Goetzmann, Ingersoll, Spiegel, and Welch 2007). In addition, Agarwal and Naik (2004) show that many equity-oriented hedge fund strategies exhibit payoffs resembling a short put option on the market index. Hence, a general concern about hedge fund leverage is that it may simply reflect the result of holding these implicit short positions. Although short positions in puts allow a fund to build up leverage—e.g., by collecting the option premium up front and investing it in other risky assets—these positions come at the cost of significant left-tail risk.

Therefore, it is important to examine whether hedge funds with high asset-implied leverage bear more left-tail risk.

The last column addresses this concern. It reports that fund companies with top-quintile leverage exhibit positive skewness and thus *lower* left-tail risk. Downside risk seems randomly distributed across the leverage quintiles. Collectively, this result rejects downside risk as an alternative channel to explain leverage-related performance and economic rents, at least for top-quintile hedge fund companies that benefit the most from leverage.

Moving to Panel B of Table 2, we investigate the economic rents of leverage. Column (1) presents the average of dynamic fees generated by hedge fund companies within each asset-implied leverage quintile. In Column (2), we present the risk-adjusted dynamic fees using Fung and Hsieh's (2004) seven-factor model. Both columns show an almost monotonic increasing pattern in dynamic fees when hedge fund companies are sorted based on past asset-implied leverage. Quintiles with higher leverage obtain higher dynamic fees compared to quintiles with lower leverage. On average, top-quintile fund companies earn 0.49% dynamic fees per quarter (or 1.98% per year), which is 42% more than what bottom-quintile fund companies collect (0.34% per quarter or 1.40% per year). This difference is both statistically significant and economically sizable. Using a value-weighted average of dynamic fees or alternative factor models does not change our results (see Panel A of Table IN1 in our Online Appendix). These results strongly support our first hypothesis that leverage enables hedge funds to obtain economic rents and retain them through dynamic fees.

The last two columns of Panel B report the risk-adjusted before-fee and after-fee returns of the sorted portfolio while controlling Fund and Hsieh's (2004) seven factors for hedge fund returns. Top-quintile fund companies generate a significant risk-adjusted before-fee performance of 1.13% per quarter, whereas bottom-quintile families make only 0.68% per quarter. This leads to an annual performance spread of 1.83%. By contrast, the spread of after-fee returns is not significant. These findings are consistent with the notion that hedge funds generate economic rents by using leverage, allowing hedge funds with top leverage to both generate the highest before-fee performance and capture these economic rents via fees.[20]

Our Online Appendix (Table IN1, Panel B) documents the transition matrix of hedge fund leverage across quintiles. We observe that hedge fund leverage is quite persistent over time. For instance, a top-quintile hedge fund company has a high probability of 89.5% of remaining in the top leverage-quintile in the next quarter. This persistence is consistent with the notion that some hedge fund companies are skillful in harnessing leverage-related benefits.

It is important to note that the asset-implied leverage is calculated as equity holdings of a fund company scaled by the AUM of all funds within the hedge fund company. This empirical strategy accounts for the possibility of using bond AUM as collateral for equity investments, thereby making bond AUM relevant to the overall leverage of a family. As a robustness check, we also use narrower definitions of asset-implied leverage by focusing solely on equity-oriented AUMs. We achieve this by utilizing three subsamples of fund AUMs to scale equity investments. The first subsample excludes fund AUMs from categories such as "Convertible Arbitrage," "Fixed Income Arbitrage," and "Managed Futures" reported by the TASS database. For other databases, we map their reported fund categories to corresponding TASS categories. In the second and more restrictive subsample, we exclude the "Global Macro," "Options Strategy," and "Fund of Funds" categories. Finally, in the most restrictive subsample, we consider only the AUMs of "Long/Short Equity" hedge funds. The Online Appendix (Table IN2) presents the sorting results of dynamic fees and seven-factor adjusted fees using these alternative leverage measures. The results demonstrate the robustness of our findings across different leverage measures. Overall, our portfolio sorting tests consistently indicate that leverage enables hedge funds to capture leverage-generated economic rents.

Since family characteristics may have an impact on leverage in our portfolio sorting tests, we perform regression analyses that control these characteristics. Specifically, we estimate a panel regression model at a quarterly frequency as follows:

---

[20] In practice, hedge funds may still share some leverage-generated economic rents with their investors. Hence, the spread of after-fee returns remains positive.

$$Dynamic\ fee_{i.t} = \alpha + \beta \times Leverage_{i,t-1} + \delta \times M_{i,t-1} + \epsilon_{i,t}, \tag{14}$$

where $Dynamic\ fee_{i.t}$ refers to the dynamic fee collected by hedge fund company i in quarter t, $Leverage_{i,t-1}$ is the asset-implied leverage of the family in the previous quarter, and the vector $M_{i,t-1}$ includes a list of hedge fund company characteristics in quarter t-1 as control variables (e.g., after-fee returns, the value of holding assets, hedge fund flows, the number of funds in the family and the number of stocks invested by the family). All specifications include hedge fund company fixed effects and time (year-quarter) fixed effects. Hence, estimation captures the within-company variation related to leverage.

The results of regression analysis are presented in Table 3. The first column shows that hedge fund dynamic fees are positively associated with lagged asset-implied leverage. The coefficient on leverage is positive and significant (T-statistic=3.54). The economic implication is that a one-standard-deviation increase in lagged leverage is associated with 14.72% (=0.01% x 5.1/0.35%) increase in dynamic fees.[21] Given the skewed distribution of leverage and dynamic fees, this magnitude likely underestimates the advantages for high-leverage families, as evidenced by our previous portfolio analysis. These findings confirm the results from the portfolio analysis and highlight the substantial benefits of leverage for hedge funds. The coefficient on the lagged fund return is positive and significant, thus, higher return in the preceding quarter is positively associated with higher dynamic fees. Finally, the coefficient on the lagged value of asset holdings is negative and significant, indicating a negative relationship between asset holdings and dynamic fees.

Columns (2) and (3) of Table 3 report the effect of leverage in two subsamples: single-fund companies and multi-fund companies. Comparing these subsamples, we find that the coefficient of leverage for single-fund companies more than doubles that of multi-fund companies, suggesting that leverage plays an even more prominent role for single-fund companies. In Columns (4) to (6)

[21] The standard deviation of asset-implied leverage ratio is 5.1% and the average quarterly dynamic fees is 0.35% (see Table 1).

of Table 3, we report results after controlling Fung and Hsieh's (2004) seven factors for hedge fund returns and find that the results are consistent with those in Columns (1)-(3). Again, the coefficient on lagged asset-implied leverage is significant and positive for the full sample, and the magnitude of this coefficient for the single-fund family subsample is larger compared to the multi-fund family subsample. These observations suggest that single-fund families better fit the leverage-fee relationship than multiple-fund companies. This difference is reasonable because multiple-fund companies face coordination issues across their affiliated funds and may adopt more complex leverage strategies. As a result, our asset-based leverage measure becomes a nosier proxy for the leverage condition of their operations.

In summary, both portfolio-based and regression-based analyses provide strong evidence to support our first hypothesis that leverage enables hedge funds to generate economic rents through dynamic fees.

B. Active Changes in Leverage and Holding Beta

We now examine how adverse investment and funding shocks, as indicated by poor past returns, affect the active leverage policy of hedge fund companies by estimating the following panel regression:

$$\Delta L_{i.t} = \alpha + \beta \times HF\ return_{i,t-1} + \delta \times M_{i,t-1} + \epsilon_{i,t}, \tag{15}$$

where $\Delta L_{i.t}$ denotes the active change in leverage of hedge fund company i in quarter t and $HF\ return_{i,t-1}$ is the lagged return of family i in quarter $t-1$. To allow for the accumulation of funding condition deterioration over a longer period, we also use lagged semi-annual returns as an independent variable. The vector $M_{i,t-1}$ includes a list of control variables as defined in Equation (14).

The regression results are presented in Table 4. Columns (1) and (2) report the effect of lagged quarter returns (labeled $HF\ return_{t-1}$ in the table) and lagged semi-annual returns (labeled $HF\ return_{\,t-1,SemiAnnual}$), respectively, on the active change in leverage for the entire sample of fund companies. In both specifications, the coefficients on lagged hedge fund returns are positive and significant (T-statistics = 3.95 and 4.90), suggesting that hedge funds actively reduce leverage when the lagged returns are poor. Among the control variables, lagged holding assets and the number of stocks are negatively associated with the active change in leverage, while the relationship is positive for lagged fund flow. Results of sub-sample analyses for single-fund and multi-fund families are tabulated in Columns (3)-(6). They are qualitatively similar to those reported for the full sample. Thus, the positive relationship between the change in leverage and lagged hedge fund returns holds for both single and multi-fund companies.

Next, we examine how adverse funding conditions affect active changes in the holding beta of hedge fund companies by estimating the following panel regression model:

$$\Delta HB_{i.t} = \alpha + \beta \times HF\ return_{i,t-1} + \delta \times M_{i,t-1} + \epsilon_{i,t}, \tag{16}$$

where $\Delta HB_{i.t}$ is the change in holding beta of company *i* in quarter *t*. All other variables are defined as in Equation (15).

The results are presented in Table 5. Columns (1) and (2) show that the change in holding beta is negatively associated with lagged hedge fund returns in the full sample, regardless of whether we use the previous quarter's return or previous 6-month return as an independent variable. We also perform the above analysis for the two sub-samples. Interestingly, Columns (3) and (5) report that the coefficient on the lagged 3-month return is negative and significant for the subsample of single-fund families but insignificant (while the coefficient is still negative) for another subsample of multi-fund families. In contrast, the coefficients on the lagged 6-month return are negative and significant for both types of families.

Overall, the results reported in Table 4 provide supporting evidence that hedge funds actively reduce (increase) leverage when realized returns reveal deteriorated (improved) funding conditions. This result is apparent for both single-fund and multi-fund families. The results in Table 5 are consistent with the prediction of our model that hedge funds actively increase (decrease) their holding betas when funding conditions deteriorate (improve). Although both types of fund families adjust holding betas according to changes in funding conditions, single-fund families do so more promptly than multi-fund families.

C. Simultaneous Changes in Leverage and Holding Beta

In this section, we investigate the extent to which hedge funds adjust their leverage and holding beta simultaneously in response to adverse shocks in funding conditions, particularly when poor performance is observed. Our previous results have provided evidence to support the hypothesis that hedge funds reduce leverage and increase holding beta in such situations.

To examine the simultaneous changes in leverage and holding beta, we introduce dummy variables to describe the four possible actions that hedge funds can take:

(1) $I\{\Delta L<0, \Delta HB>0\}$, a dummy variable that takes a value of one if a hedge fund company reduces leverage and increases holding betas simultaneously;
(2) $I\{\Delta L>0, \Delta HB>0\}$, a dummy variable that takes a value of one if the company increases leverage and holding betas simultaneously;
(3) $I\{\Delta L>0, \Delta HB<0\}$, a dummy variable that takes a value of one if the company increases leverage and decreases holding betas simultaneously; and
(4) $I\{\Delta L<0, \Delta HB<0\}$, a dummy variable that takes a value of one if the company decreases leverage and holding betas simultaneously.

We find that each scenario occurs with nearly equal likelihood of 25% throughout fund operations. However, our model predicts that only scenarios (1) and (3), in which leverage and beta move in opposite directions, occur when funds face adverse shocks in funding conditions. To test this prediction, we regress these dummy variables on lagged fund returns using the following panel regression:

$$D\{Simultanuous\ Change\}_{i.t} = \alpha + \beta \times HF\ return_{i,t-1} + \delta \times M_{i,t-1} + \epsilon_{i,t}, \quad (17)$$

where $D\{Simultanuous\ Change\}_{i.t}$ denotes one of the four dummy variables for hedge fund company i in quarter t. We use lagged fund return as an independent variable but with two modifications. First, we use the lagged semiannual return as the independent variable since our previous results suggest that it takes longer (up to 6 months) for multi-fund companies to adjust holding beta. Second, we decompose semi-annual returns into two signed components to assess whether hedge funds react differently to positive and negative past performance. The positive part is calculated as $HF\ return^{+} = HF\ return \times I\{HF\ return > 0\}$, where $I\{.\}$ is an indicator function. That is, $HF\ return^{+} = HF\ return$ when $HF\ return > 0$ and zero when the realized return is negative. Likewise, the negative part of the returns is calculated as $HF\ return^{-}$=$HF\ return \times I\{HF\ return \leq 0\}$. Each of the four dummy variables is regressed on the positive and negative parts of lagged hedge fund returns.

In Panel A of Table 6, we present the results for the full sample, with each column representing one of the four dummy variables as the dependent variable. The most notable findings are reported in Columns (1) and (3). Column (1) reports a significant and negative coefficient on lagged negative fund returns (labeled $HF\ return^{-}_{t-1,SemiAnnual}$ in the table). This result indicates that hedge funds simultaneously reduce leverage and increase holding betas following periods of negative returns in the previous two quarters.

Moreover, the negative coefficient suggests that the more negative the returns are, the more likely hedge funds are to adopt the strategy of reducing leverage and increasing holding beta. Roughly speaking, each 1% additional negative return increases these adjustments by 0.33%. These results provide evidence to support our second hypothesis. In contrast, the coefficient on the positive part of the return, $HF\ return^{+}_{t-1,SemiAnnual}$, is insignificant, suggesting that positive lagged fund returns do not affect the simultaneous changes in leverage and betas in this case. In other words, the simultaneous deleverage policy is predominantly used in response to negative return shocks, which indicates deteriorating funding conditions.

Column (3) of Panel A reports that lagged fund returns affect policies of simultaneous leverage increase and holding beta decrease. We notice that the coefficient of $HF\ return^{-}_{t-1,SemiAnnual}$ is positive and significant. Since $HF\ return^{-}_{t-1,SemiAnnual}$ carries a negative sign, a positive coefficient suggests that more negative lagged returns reduce the likelihood of hedge funds increasing leverage and decreasing beta. Furthermore, positive shocks ($HF\ return^{+}_{t-1,SemiAnnual}$) increase the likelihood of simultaneous leverage increase and holding beta decrease. These results support the predictions of our model.

Panel A of Table 6 also provides results for the two scenarios when changes in leverage and beta are in the same direction. Columns (2) and (4) indicate that past returns do not affect simultaneous changes in leverage and beta in this case. This result is reasonable as these policies, although prevalent in the data, are unrelated to the effects studied in our model.

Panels B and C of Table 6 present results for single-fund families and multi-fund families. Regarding simultaneous policy changes in opposite directions, single-fund families appear to be more affected by positive lagged returns, while multi-fund families are more affected by negative lagged returns. Moreover, the effect remains largely insignificant for simultaneous changes in leverage and beta that are in the same direction. Taken together, these results reveal a difference between policy changes in the same direction and those in opposite directions.

Finally, we conduct the same analysis using a narrower definition of leverage. In the Online Appendix (Table IN3), we present the results when asset-implied leverage is constructed based on a sample excluding funds in the "Convertible Arbitrage," "Fixed Income Arbitrage," and "Managed Futures" categories. The results confirm that hedge funds still simultaneously adjust leverage and beta policies and that our findings are robust to alternative leverage measures.

Overall, the results presented in this section and the previous section provide support for Proposition 2, which posits that adverse shocks in funding conditions, as indicated by poor fund performance, lead hedge funds to simultaneously reduce leverage and increase holding beta.

IV. Asset Pricing Implications

This section explores the asset pricing implications of leverage in delegated portfolio management and examines whether hedge fund holding beta can serve as a priced risk factor in the economy.

A. The Hedge Fund *DLCT* Factor

We construct a leverage constraint tightness factor from hedge fund holding betas, following the methodology of Boguth and Simutin (2018). In our model, hedge fund holding betas serve as a proxy for a priced factor due to the observed negative relationship between leverage and beta. Empirically, hedge fund beta provides a more precise measure than leverage to assess the tightness of hedge fund leverage constraints. [22] We refer to our factor as the hedge fund delegated leverage constraint tightness (*DLCT*) factor.

To construct the *DLCT* factor, we value-weight hedge fund company holding betas as follows:

$$HF\_beta_t = \sum\nolimits_s \frac{holding\ value_{HF,s,t}}{\sum_s holding\ value_{HF,s,t}} \times stock\ beta_{s,t}\,, \tag{18}$$

where $holding\ value_{HF,s,t}$ refers to the aggregated value of shares held by all hedge fund companies for stock s in month t, and $stock\ beta_{s,t}$ is the market beta of the stock s estimated from the stock's daily returns within month t. When estimating betas, we adjust for asynchronous trading using the method of Dimson (1979) and Lewellen and Nagel (2006).

Given that the leverage of single-fund companies is better grounded and measured, we aggregate the holding betas of these families as our primary empirical proxy. Specifically, we estimate an AR(1) model that regresses HF_beta_t on HF_beta_{t-1} using all available data up to and including month t to avoid any look-ahead bias. We refer to the innovations derived from the AR(1) model as the *DLCT factor* (or $\Delta_t^{HF\_beta}$). As a robustness check, we will use all hedge fund companies to construct an alternative factor and report results in a later section. This alternative factor does not alter our main conclusions because all hedge fund companies are likely to face common investment opportunities and frictions related to delegated leverage.

We present evidence in Table IN4 to show that well-known risk factors are unable to explain the *DLCT* factor. Specifically, we estimate time-series regressions by regressing the *DLCT* factor

[22] This is because many leverage instruments used by hedge funds are not observable, which adds noise to the asset-implied leverage measure. On the other hand, hedge fund equity holdings as well as the corresponding holding beta can be measured with greater accuracy.

on the Fama and French (1993) three factors, including the market (Mkt-RF), size (SMB) and value (HML) factors, as well as Carhart's (1997) momentum and Pastor and Stambaugh's (2003) liquidity factors. The results in Columns (1) and (4) show that these risk factors are not significant and there is no overlapping between the *DLCT* and the well-known risk factors.

We also regress the *DLCT* factor on several funding liquidity factors, including the Intermediary Capital Risk factor (He, Kelly and Manela 2017), the 3-month LIBOR Rate (Ang, Gorovyy and van Inwegen 2011), the percentage of loan officers tightening credit standards for commercial and industrial loans – the Loan Tighten factor (Lee 2013), the Term Spread (Ang, Gorovyy and van Inwegen 2011), the TED Spread (Gupta and Subrahmanyam 2000), the Credit Spread (Adrian, Etula and Muir 2014), the VIX index (Ang, Gorovyy and van Inwegen 2011), the mutual fund LCT factor (Boguth and Simutin 2018), and the betting-against-beta (BAB) factor (Frazzini and Pedersen 2014).

While the single-family *DLCT* factor exhibits a significant correlation with the credit spread and VIX, the significance diminishes when considering the all-family *DLCT* factor. Next, although the mutual fund LCT factor shows a significant correlation with the *DLCT* factor, the joint explanatory power of funding liquidity factors, mutual fund LCT, and BAB on the single-family DLCT factor only amounts to 34.4%. In other words, these factors fail to explain the majority of time variation in this *DLCT* factor. Even for the noisier all-family *DLCT* factor, the joint explanatory power is still below half.

Collectively, these findings strongly suggest that the *DLCT* factor captures a novel state variable that extends beyond the scope of existing asset pricing and funding liquidity factors. Economically speaking, the *DLCT* factor differs from traditional factors because it reflects the tightness of capital from the demand side, specifically from hedge funds. In contrast, known funding liquidity factors either come from the supply side (e.g., the intermediary factor) or reflect the equilibrium prices (e.g., the TED spread) that synchronize both demand and supply. The only factor from the demand side is mutual fund LCT, which explains its relatively high correlation with the DLCT factor. However, even this factor can only explain a small portion of *DLCT* time variation because, among other reasons, hedge funds and mutual funds play very different economic roles during high-stress periods, as we will show later.

B. Portfolio Analysis

In this section, we examine whether the *DLCT* factor is priced in the cross-section of stock returns. We conduct portfolio analysis by sorting stocks into quintiles based on their return exposure to the factor. $Exposure^{DLCT}$ is the time-series loadings of each stock on the *DLCT* factor, which we estimate using a 12-month rolling regression of the stock's excess returns on market excess returns and the *DLCT* factor. Then stocks are assigned into five groups at the end of each month t, and the equal-weighted portfolios are held in month $t + 1$. We report the performance of these portfolios in Table 7.

Examining the average excess return of the five portfolios, we find a decreasing pattern in excess returns associated with stocks' exposure to the *DLCT* factor. The bottom quintile, which is comprised of stocks with the lowest exposure, has an average excess return of 0.94% per month, with a T-statistic of 2.61. In contrast, the top quintile displays a significantly lower average excess return of 0.36% per month, with a T-statistic of 1.02. A strategy that takes a long position in the bottom portfolio and a short position in the top portfolio (i.e., Low-minus-High) generates a significant return spread of 0.58% per month (or, 7.2% per year).

We also estimate the alphas of the portfolios using different factor models (e.g., the CAPM model, the Fama-French three-factor model, the Carhart four-factor model and the Pastor and Stambaugh five-factor model) The return spread between portfolios with high and low factor exposure remains significant both statistically and economically. For instance, the risk-adjusted return spread for the Low-minus-High strategy is 0.56% per month (or, 6.9% per year), using the Fama-French three-factor model. Moreover, alphas of the Carhart four-factor model and the Pastor-Stambaugh liquidity augmented five-factor model have similar economic magnitudes. These findings provide compelling evidence to support the hypothesis that the *DLCT* factor, which is derived from hedge fund holdings, captures a distinct economic dimension that significantly influences stock returns.

C. Cross-Sectional Analysis

We conduct Fama-MacBeth regression analysis to test whether the *DLCT* factor is priced in the cross-section of stock returns. Every month, we regress stock return in month $t + 1$ on the stocks' exposure to the *DLCT* factor ($Exposure^{DLCT}$). As before, $Exposure^{DLCT}$ is estimated for each stock from a 12-month rolling window ended in month t. We also include a list of characteristics that are known to affect stock returns, including the stock's lagged market equity, book-to-market ratio, profits-to-assets ratio, asset growth rate, stock return run up, reversals, and idiosyncratic volatility. All independent variables, as defined in Appendix A, are normalized to have a cross-sectional standard deviation of one. Thus, the regression coefficients indicate the return predictivity associated with a one-standard-deviation change in stock characteristics.

The results are presented in Table 8. The coefficients of $Exposure^{DLCT}$ are consistently negative and significant across all specifications. This result indicates that higher exposure to the hedge fund *DLCT* factor predicts significantly lower returns. For instance, in Column (1), the coefficient of $Exposure^{DLCT}$ is –0.19 with a significant T-statistic of –3.41. This implies that a one-standard-deviation increase in the stock's exposure to the *DLCT* factor corresponds to a 0.19% reduction in the monthly stock return (or 2.27% in annualized return).

Additional characteristics do not absorb the predictive power of the *DLCT* factor loading. The economic magnitude ranges from 1.13% in Column (6) to 2.27% per annum in Column (4). Collectively, these results provide support to Hypothesis 3A that the *DLCT* factor is priced in the cross-section.

V. Analyses of Alternative Mechanisms

Thus far, we have shown that leverage provides an important rationale for the creation of hedge funds and that its associated *DLCT* factor has significant power to predict stock returns in the cross-section. This section conducts a battery of analyses to further investigate these economic mechanisms. We first explore the potential impact of limited partners' leverage on fund policies. Next, we examine whether the pricing power of hedge fund *DLCT* factor is concentrated in states with reduced hedge fund leverage, as predicted by our model. Lastly, we utilize the Lehman bankruptcy event to illustrate how stocks were exposed to our *DLCT* factor through hedge fund ownership.

A. The Impact of LP Leverage on Fund Policies

We start with alternative explanations of hedge fund policies. It is important to note that our model is built upon the assumption that investor capital is competitively supplied in the market and that this assumption allows fund managers to capture the economic rents (Berk and Green, 2004). An alternative channel is that investors may have different preferences regarding leverage. In the presence of such heterogeneous investors, fund policies, including fees, could also be affected. Indeed, Hitzemann, Sokolinski, and Tai (2022) find evidence suggesting that investor leverage demand allows mutual fund managers to charge higher fees. Could investors' leverage preferences play a similarly important role within the hedge fund industry to overturn our model predictions?

We use the information provided by the Preqin database on limited partners (LPs) to answer this question. Preqin reports how LPs invest in general partners (GPs) within the hedge fund industry. In our analysis, LPs represent hedge fund investors and GPs correspond to hedge fund companies. We manually match the names of Preqin GP with those in the merged TASS-HFR-BarclayHedge database and construct a sample of LPs investing in hedge fund companies. We then calculate each LP's leverage as the average leverage employed by the hedge fund companies in which the LP has made investment. If an LP possesses a specific leverage preference, the average leverage of the hedge fund companies she has invested in indicates—in a revealed preference approach—her leverage preference.

This measure allows us to link hedge fund fee policies to the average LP leverage for each hedge fund company, with the latter serving as the representative LP's leverage preference faced by fund managers. We tabulate results in Online Appendix (Table IN5) and discuss main findings here.[23] The average LP leverage ratio is 4.45 and the median is 2.74. We observe that, in isolation, LP leverage does not affect the fee policies of hedge funds (see Panel A). Even when we interact LP leverage with hedge fund leverage or fund flows, the interactive terms are still insignificant. Similarly, hedge fund flow and its interaction with hedge fund leverage fail to impact fee policies. Panel B presents results when we use the Fung and Hsieh's seven-factor adjusted dynamic fees as the dependent variable. The results are similar to those reported in Panel A. Collectively, investors do not play an active role in shaping hedge fund fee policies, even though there is a difference in the limited partners' preference for leverage.

Next, we examine the impact of LP leverage on simultaneous and opposite leverage-beta adjustments. We present results in Online Appendix (Table IN6) and discuss the main findings here. For the case of deleveraging (i.e., I{ΔL<0, ΔHB>0}), LP leverage once again has insignificant effects when used alone or when interacted with the negative part of past returns (i.e., $HF\ return^{-}_{t-1,SemiAnnual}$).[24]

For the case of leverage increases (i.e., I{ΔL>0, ΔHB<0}), LP leverage has insignificant effects on the above indicator variable when used alone or when interacted with the positive component of past returns. The interactive term between LP leverage and the negative component of past returns has a negative and significant coefficient. However, the economic magnitude of this effect is modest. Even an LP leverage of 10 only offsets 37% of the return impact, implying the limited influence of LPs on hedge fund leverage policies.

In summary, our findings suggest that LP leverage does not have a significant impact on fee policies within the hedge fund industry. This implies that investor capital is competitively supplied in the hedge fund industry when fund managers determine the fee policies–a conclusion that aligns with the key assumption of Berk and Green (2004) and our model. We leave the exploration of the remaining bargaining power of LPs to future research.

---

[23] Preqin contains the information for approximately 5935 funds, out of which 1924 can be identified as hedge funds covered by our databases. Approximately 38% of hedge fund families have valid LP information. To ensure a comparable sample size, we use a dummy variable I{LP Info} to absorb the fee policies of families for which there is no LP information.

[24] Although we observe a negatively significant interaction between LP leverage and the positive component of past returns, its coefficient is economically small (0.0012). For instance, even an LP leverage of 10 can only add 0.012 to the impact of positive returns, which is negligible compared to the impact of negative returns (which is 0.346 in this regression).

B. Controlling Penny Stocks and Mutual Fund LCT Factor

In this section, we address concerns that the pricing power of beta-related factors may be driven by penny stocks. Among all the stocks in our sample, approximately 4% of them are penny stocks. To alleviate this concern, we exclude all the penny stocks from our sample and re-conduct the Fama-MacBeth regression analysis. The results are reported in Column (1) of Table 9. Even after excluding penny stocks, the coefficient of $Exposure^{DLCT}$ remains negative and significant, and has a magnitude similar to that reported in Column (6) of Table 8.

In Column (2) of Table 9, we control for the mutual fund LCT factor proposed by Boguth and Simutin (2018).[25] Specifically, we include stocks' exposure to the mutual fund LCT factor ($Exposure^{MF\_LCT}$) in the Fama-MacBeth regressions, alongside their exposure to our hedge fund *DLCT* factor ($Exposure^{DLCT}$). We find that the coefficient of $Exposure^{DLCT}$ remains negative and significant, with a magnitude on par with previous results. Unreported results also show that the predicting power of the hedge fund DLCT factor is not affected by stocks' exposure to the bet-against-beta (BAB) factor of Frazzini and Pedersen (2014).

Overall, these results indicate that the pricing power of the hedge fund *DLCT* factor remains robust when controlling for penny stocks. In addition, this factor captures distinct economic information beyond that explained by the mutual fund LCT factor.

C. The Pricing Power of *DLCT* Conditioning on Hedge Fund Leverage

We now move on to the additional prediction unique to our model as stated in Hypothesis 3. That is, the pricing power of the hedge fund beta factor should be concentrated in states with reduced hedge fund leverage. To test this hypothesis, we estimate the AUM-weighted aggregate leverage of the hedge fund industry as $HF_{Leverage_{LCT,t}} = \sum_i \frac{AUM_{i,t}}{\sum_i AUM_{i,t}} \times L_{i,t}$, where $AUM_{i,t}$ refers to AUM of company i in quarter t. We then estimate the innovations in hedge fund industry leverage using an AR(1) process, which allows us to identify periods when this leverage measure is relatively

[25] We thank Boguth and Simutin for making their LCT factor available. We employ their published mutual fund LCT factor whenever possible. For later periods spanning from 2015 to 2019, we extend the factor using their methodology.

tightened. Specifically, we divide our sample period into two subperiods: one characterized by reduced hedge fund leverage (below-medium innovations) and the other by enhanced hedge fund leverage (above-medium innovations).

We revisit the Fama-MacBeth regressions in each sub-period, excluding penny stocks from our sample, and report results in Columns (3) and (4) of Table 9. The coefficient of the variable $Exposure^{DLCT}$ (e.g., stocks' exposure to the *DLCT* factor) is negative, but only significant in the subperiod with reduced hedge fund leverage. Thus, the pricing power of the hedge fund *DLCT* factor is concentrated in periods in which hedge funds reduce their leverage.

D. Alternative Hedge Fund *DLCT* Factor

So far, our empirical proxy for the hedge fund *DLCT* factor is constructed by aggregating the holdings of single-fund companies, and this proxy is a cleaner one. As a robustness check, we use the holdings of all hedge fund companies to construct an alternative *DLCT* factor. The Fama-MacBeth regression results are presented in the Online Appendix (Table IN7). Across all specifications, we find that the coefficients of the alternative hedge fund *DLCT* factor are negative and significant after controlling for other firm characteristics. Hence, using the holdings of all hedge fund companies to construct the asset-implied leverage and the *DLCT* factor does not change our main conclusions, because all hedge fund companies are subject to common shocks of delegated leverage.

E. The Lehman Bankruptcy Event

We investigate the asset pricing impact of hedge fund leverage by taking a closer look at the Lehman bankruptcy that occurred on September 15, 2008. Aragon and Strahan (2012) document that hedge funds using Lehman as a prime broker faced a decline in funding liquidity after its bankruptcy. As a result, this event unexpectedly disrupted trading and hindered access to funding for Lehman-connected hedge funds. This episode serves as an ideal laboratory, in which a funding shock exogenously tightens the capital for delegated leverage.

Although many institutional investors face leverage constraints, hedge funds, as quintessential levered investors, play a unique role in affecting asset prices during this episode through two economic channels. Our previous tests show that the *DLCT* factor exhibits more pronounced pricing power during such distressed periods. In addition, disruptions in hedge fund capital may also affect the exposure of hedge fund-invested stocks to the hedge fund *DLCT* factor. Since this second channel is novel, we will use the Lehman shock to investigate it.

Hypothetically, stocks held by Lehman-connected funds should be more susceptible to the *DLCT* factor that captures the aggregate funding shock. This is because the Lehman bankruptcy directly disrupted the flow of capital from leveraged investors to these stocks, which subsequently affected stock returns, reduced the co-movement of an affected stock to the market, and increased its co-movement with other stocks similarly affected by the disruption.[26] In other words, in addition to a higher level of capital tightness created by the Lehman shock across the entire economy, stocks held by Lehman-connected hedge funds should particularly experience a greater impact manifested through enhanced exposure to the *DLCT* factor.

To test this hypothesis, we examine the relationship between stocks' exposures to the *DLCT* factor and their holdings by Lehman-connected hedge funds in the following pooled regression:

$$\begin{aligned} \Delta Exposure_{i,t}^{DLTC} &= \alpha + \beta_1 \times Lehman\ HF\ holdings_{i,2008.06} \\ &+ \beta_2 \times Non_{Lehman} HF\ holdings_{i,2008.06} + \beta_3 \times MF\ holdings_{i,2008.06} \\ &+ \beta_4 \times Other\ Institutional\ holdings_{i,2008.06} + \epsilon_{i,t}, \end{aligned} \tag{19}$$

where $\Delta Exposure_{i,t}^{DLTC}$ refers to the change in the exposure of stock i to the *DLCT* factor in month t. It is calculated as the stock's exposure to the *DLCT* factor estimated from daily returns in month t minus its exposure in the previous month. $Lehman\ HF\ holdings_{i,2008.06}$ refers to the percentage of shares of stock *i* held by Lehman-connected hedge funds in June 2008, as defined in

[26] Mathematically, Equation (6) of our model suggests that the exposure of a particular stock to the aggregate *DLCT* factor is $1 - \beta$, where $\beta = cov(R_e, R_{MKT})/var(R_{MKT})$ is the covariance between the stock returns and the market return. When the Lehman disruption disturbs the stock returns, it reduces the market beta of the stock and increases its exposure to the aggregate *DLCT* factor. Since we do not explicitly model the impact of deteriorating funding conditions on β, we interpret this effect as an empirical implication consistent with our model rather than a direct prediction of it.

Aragon and Strahan (2012). We also include the percentage of shares of stock *i* held by non-Lehman-connected hedge funds (Non-Lehman HF holdings), the percentage of shares of stock *i* held by mutual funds (MF holdings), and the percentage of shares of stock *i* held by other types of institutions (Other-Institutions holdings) in June 2008. Time (year-month) fixed effects are included to control for the overall market conditions each month.

The results are reported in Table 10. The first three columns show the impact of Lehman-connected hedge fund holdings in three consecutive periods: January to April, May to August, and September to December of 2008. The last period corresponds to the Lehman bankruptcy period. We examine the three periods separately because the first two periods provide an ideal placebo test for validating our results during the Lehman bankruptcy period.

Our main findings are threefold. First, we observe that the coefficient of Lehman-connected hedge fund holdings is positive and significant during—and only during—the Lehman bankruptcy period. Economically, this result indicates that greater holdings by Lehman-connected hedge funds in June 2008 significantly increased a stock's exposure to the hedge fund *DLCT* factor. As a placebo test, we further observe that non-Lehman-connected hedge fund ownership does not exhibit a similar effect. This insignificance highlights the differences between Lehman- and non-Lehman-connected hedge funds during the period of stress during Lehman's bankruptcy.

Second, the coefficients on mutual fund holdings and other institutional holdings are significant during the Lehman bankruptcy period. However, these coefficients have the opposite sign compared to that of Lehman-connected hedge fund holdings, suggesting that mutual funds and other non-hedge fund institutions mitigated the impact of Lehman-connected hedge funds. In other words, when Lehman-connected hedge funds suffered from the funding shock, mutual funds and other institutional investors stepped in to supply capital, helping to stabilize the market. It is worth noting that, in economic terms, the coefficient on hedge fund holdings is five times larger than that of mutual fund holdings. Hence, mutual funds and other institutions only partially alleviate the impact of Lehman-connected hedge funds. This difference suggests that hedge funds are an important marginal investor to affect asset prices.

Third, in Column (4) of Table 10, we provide another placebo test by replacing the hedge fund *DLCT* factor with the mutual fund LCT factor during the Lehman bankruptcy period. The results indicate that Lehman-connected hedge fund ownership does not affect stock's exposure to mutual fund LCT. This finding supports the notion that the hedge fund *DLCT* factor effectively captures the market-wide price impact of the tightness of leverage constraints during the specific period of the Lehman bankruptcy, considering the known liquidity challenges posed by Lehman-connected hedge funds for stocks.

Taken together, our tests concerning Lehman's bankruptcy shed light on how stocks become susceptible to a large aggregate funding shock. The three main results suggest that hedge funds and mutual fund-type non-hedge fund institutional investors play very different roles during high-stress periods such as Lehman's bankruptcy. Overall, the Lehman event identifies a unique role that hedge funds play in affecting assets through the risk exposure channel during a period of substantial funding shocks.

VI. Conclusion

This paper examines how leverage affects asset prices via delegated portfolio management. Our intuition is that capable investors exploit their leverage advantage through delegated portfolio management in the spirit of Berk and Green (2004), rather than directly employing leverage (within exogenously determined constraints) to enhance the return of their own endowed capital. We formulate this intuition into a stylized model in which a hedge fund raises capital from constrained investors to exploit its leverage advantage, which provides an economic rationale for leverage-based delegated portfolio management. Our model suggests that fund managers reap the totality of these economic rents. This perspective also helps explain the otherwise puzzling empirical observation that the relationship between leverage and performance of hedge funds is insignificant, as reported in previous studies. Furthermore, asset prices are influenced by the tightness of capital constraints faced by hedge fund managers.

We test a collection of novel predictions of the effects of leverage on delegated portfolio management and asset prices. First, in line with our model, we find that hedge funds with higher asset-implied leverage collect higher fees. Second, deteriorating funding conditions—proxied by recent poor fund returns—prompt hedge funds to *simultaneously* reduce leverage and increase their holdings in high-beta stocks. The above results enable us to construct a risk factor, the hedge fund delegated leverage constraint tightness (*DLCT*) factor, based on hedge fund holding betas. We demonstrate that the *DLCT* factor explains the cross-section variation of stock returns, with its pricing power concentrated in periods characterized by reduced hedge fund leverage. Furthermore, our case study on the Lehman bankruptcy highlights how hedge fund investment impacts stock exposure to the *DLCT* factor during periods of distress.

In summary, our analyses propose that hedge funds can be viewed as mechanisms for delegated leverage and validate their importance in determining asset prices. These results provide an economic basis by which to understand hedge fund incentives and fee policies. They also allow us to construct a priced risk factor, the hedge fund *DLCT* (the delegated leverage constraint tightness) factor, that affects expected stock returns and has explanatory power above and beyond existing factors. Compared to the traditional approach of proposing factors from model premises, the provision of an asset pricing factor grounded in a concrete micro foundation has the advantage that it can be subject to both theoretical and empirical scrutiny. Our empirical results suggest that leverage-motivated delegated portfolio management in general, and the leverage choice of hedge funds in particular, play an important role in financial markets.

Reference

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557-2596.

Agarwal, Samanvaya, 2021, Hedge fund leverage: The role of moral hazard and liquidity insurance, Working paper, https://ssrn.com/abstract=3977431.

Agarwal, Vikas, and Narayan Y. Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17, 63–98.

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2009, Role of Managerial Incentives and Discretion in Hedge Fund Performance, *Journal of Finance* 64, 2221-2256.

Ang, Andrew, Sergiy Gorovyy, and Gregory B. van Inwegen, 2011, Hedge fund leverage. *Journal of Financial Economics* 102, 102-126.

Aragon, George O., A. Tolga Ergun, and Giulio Girardi, 2022, Hedge fund liquidity management: Insights for fund performance, Working paper, https://ssrn.com/abstract=3734596.

Aragon, George O., and Philip E. Strahan, 2012, Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy, *Journal of Financial Economics* 103, 570-587.

Asness, Cliff, Andrea Frazzini, Niels Joachim Gormsen, and Lasse Heje Pedersen, 2020, Betting against correlation: Testing theories of the low-risk effect, *Journal of Financial Economics* 135, 629-652.

Banque de France, 2007, Financial stability review: Special issue on hedge funds.

Barth, Daniel, Laurel Hammond, and Phillip Monin, 2020, Leverage and Risk in Hedge Funds, Working paper, https://ssrn.com/abstract=3544304.

Berk, Jonathan B., and Jules H. van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1-20.

Berk, Jonathan B., and Jules H. van Binsbergen, 2017, Mutual funds in equilibrium, *Annual Review of Financial Economics* 9, 147-167.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.

Black, Fischer, 1972, Capital market equilibrium with restricted borrowing, *Journal of business* 45, 444-455.

Black, Fischer, 1993, Return and the beta, *Journal of Portfolio Management* 20, 8-18.

Boguth, Oliver, and Mikhail Simutin, 2018, Leverage constraints and asset prices: Insights from mutual fund risk taking, *Journal of Financial Economics* 127, 325-341.

Brown, Stephen, William Goetzmann, Bing Liang, and Christopher Schwarz, 2008, Mandatory disclosure and operational risk: Evidence from hedge fund registration, *Journal of Finance* 63, 2785–2815.

Brown, Stephen, William Goetzmann, Bing Liang, and Christopher Schwarz, 2009, Estimating operational risk for hedge funds: The ω score, *Financial Analysts Journal* 65, 43–53.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Brunnermeier, Markus K., and Stefan Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance* 59, 2013-2040.

Cao, Charles, Grant Farnsworth, and Hong Zhang, 2021, The economics of hedge fund startups: Theory and empirical evidence, *Journal of Finance* 76, 1427-1469.

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

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial*

Economics 7, 197-226.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fleckenstein, Matthias, and Francis A. Longstaff, 2020, Renting balance sheet space: Intermediary balance sheet rental costs and the valuation of derivatives, *Review of Financial Studies* 33, 5051-5091.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1-25.

Fung, William, and David A. Hsieh, 2004, Hedge fund benchmarks: A risk-based approach, *Financial Analysts Journal* 60, 65-80

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2018, Efficiently inefficient markets for assets and asset management, *Journal of Finance* 73, 1663–1712.

Goetzmann, William, Jonathan Ingersoll, Matthew Spiegel, and Ivo Welch, 2007, Portfolio Performance Manipulation and Manipulation-proof Performance Measures, *Review of Financial Studies* 20, 1503–1546.

Griffin, John M., and Jin Xu, 2009, How smart are the smart guys? A unique view from hedge fund stock holdings, *Review of Financial Studies* 22, 2531-2570.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393-408.

Gupta, Anurag, and Marti G. Subrahmanyam, 2000, An empirical examination of the convexity bias in the pricing of interest rate swaps, *Journal of Financial Economics* 55, 239-279.

He, Zhiguo, and Arvind Krishnamurthy, 2012, A Model of Capital and Crises, *Review of Economic Studies* 79, 735–777.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732-770.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1-35.

Hitzemann, Steffen, Stanislav Sokolinski, and Mingzhu Tai, 2022, Paying for beta: Leverage demand and asset management fees, *Journal of Financial Economics* 145, 105-128.

Jorion, Philippe, and Christopher Schwarz, 2014, Are hedge fund managers systematically misreporting? Or not? *Journal of Financial Economics* 111, 311–327.

Jylhä, Petri, 2018, Margin requirements and the security market line, *Journal of Finance* 73, 1281-1321.

Jylhä, Petri, and Matti Suominen, 2011, Speculative capital and currency carry trades, *Journal of Financial Economics* 99, 60-75.

Kisin, Roni, and Asaf Manela, 2016, The shadow cost of bank capital requirements, *Review of Financial Studies* 29, 1780-1820.

Koijen, Ralph SJ, and Motohiro Yogo, 2016, Shadow insurance, *Econometrica* 84, 1265-1287.

Lan, Yingcong, Neng Wang, and Jinqiang Yang, 2013, The economics of hedge funds, *Journal of Financial Economics* 110, 300-323.

Lee, Jaehoon, 2013, Funding liquidity and its risk premium, Working paper, https://ssrn.com/abstract=1795480.

Lewellen, Jonathan, and Stefan Nagel, 2006, The conditional CAPM does not explain asset-pricing anomalies, *Journal of Financial Economics* 82, 289-314.

Liang, Bing, and Liping Qiu, 2019, Hedge fund leverage: 2002–2017, *European Financial Management* 25, 908-941.

Lo, Andrew W., 2008, Hedge funds, systemic risk, and the financial crisis of 2007-2008: Written testimony for the house oversight committee hearing on hedge funds, Working paper, https://ssrn.com/abstract=1301217.

Lu, Zhongjin, and Zhongling Qin, 2021, Leveraged funds and the shadow cost of leverage constraints, *Journal of Finance* 76, 1295-1338.

Pástor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

Teo, Melvyn, 2011, The liquidity risk of liquid hedge funds, *Journal of Financial Economics* 100, 24–44.

Yin, Chengdong, and Xiaoyan Zhang, 2023, Risking or derisking: How management fees affect hedge fund risk-taking choices, *Review of Financial Studies* 36, 904-944.

Appendix A: Variable Definitions

Panel A: Hedge Fund Company-Level Variables

Assets	The aggregated holding assets (from 13F) of the hedge fund company i in quarter t $Asset_{i,t} = \sum_s holding\ value_{i,s,t}$, where holding value is the value of shares held by hedge fund company i in stock s in quarter t.
AUM	The aggregated AUM (assets under management) of hedge fund company i in quarter t
HF Return	The value-weighted returns of all hedge funds of hedge fund company i in quarter t
HF Flow	The capital flow ratio for each hedge fund company in quarter t based on its performance and AUM: $\left(AUM_{i,t} - AUM_{i,t-1} \times \left(1 + r_{i,t}\right)\right) / \left(AUM_{i,t-1} \times \left(1 + r_{i,t}\right)\right)$.
N_Funds	The number of funds in the hedge fund company
N_Stocks	The log number of stocks held by the hedge fund company
Leverage	Leverage refers to the asset-implied leverage for the hedge fund company (family) i in quarter t, calculated as the ratio between the family's holding value as reported by 13F and the AUM of its affiliated funds. Mathematically, $L_{i,t} = \frac{Assets_{i,t}}{AUM_{i,t}} = \frac{\sum_s holding\ value_{i,s,t}}{AUM_{i,t}}$.
Active Leverage Change	The active change of hedge fund company i's leverage in quarter t, calculated as $\Delta L_{i.t} = (L_{i,t} - \bar{L}_{i,t})/L_{i,t-1}$, where $\bar{L}_{i,t}$ is the counterfactual leverage calculated as $\bar{L}_{i,t} = \frac{\sum_s holding\ value_{i,s,t-1} \times (1+stock\ return_{s,t})}{AUM_{i,t-1}}$.
Holding Beta	The average stock beta of the hedge fund company i's aggregate holdings in quarter t, calculated as $HB_{i,t} = \sum_s \frac{holding\ value_{i,s,t}}{\sum_s holding\ value_{i,s,t}} \times stock\ beta_{s,t}$, where $stock\ beta_{s,t}$ is the monthly beta of each stock, estimated from daily returns within month t, and is based on Dimson (1979) sum betas using the lag structure suggested by Lewellen and Nagel (2006), which helps to mitigate the effects of asynchronous trading.
Active Holding Beta Change	The active change of hedge fund company i's holding beta i in quarter t, calculated as $\Delta \mathrm{HB}_{i,t} = HB_{i,t} - \overline{HB}_{i,t}$, where $\overline{HB}_{i,t}$ is the counterfactual holdingbeta, $\overline{HB}_{i,t} = \sum_s \frac{holding\ value_{i,s,t-1} \times (1+stock\ return_{s,t})}{\sum_s holding\ value_{i,s,t-1} \times (1+stock\ return_{s,t})} \times stock\ beta_{s,t-1}$.

Panel B: Aggregate Level Variables or Stock Variables

DLCT	The hedge fund *delegated leverage constraint tightness* factor. We first estimate the weighted sum of market betas of individual stocks in aggregated hedge funds' holdings as $HF\_beta_t = \sum_s \frac{holding\ value_{HF,s,t}}{\sum_s holding\ value_{HF,s,t}} \times stock\ beta_{s,t}$, where $holding\ value_{HF,s,t}$ is the aggregated value of shares held by the aggregate (single-fund) hedge fund companies in stock s in month t and $stock\ beta_{s,t}$ is the monthly beta of each stock, estimated from daily returns within month t. The beta estimation method follows Boguth and Simutin (2018), which adjusts asynchronous trading based on the approach of Dimson (1979) and Lewellen and Nagel (2006). Given that the leverage of single-fund companies is better grounded and measured, we aggregate the holding betas of these families as our main empirical proxy. We then follow the literature (Boguth and Simutin, 2018) to construct the DLCT factor as the innovations in an AR(1) regression of HF_beta_t.
MF_LCT	MF_LCT is the aggregate mutual fund beta, which is estimated from mutual fund holding betas following the methodology of Boguth and Simutin (2018).

HF_Leverage_DLCT	HF_Leverage_DLCT is the aggregate hedge fund leverage, which is estimated by the weighted sum of leverage of individual hedge funds. I.e., $DLCT_t^{HF\ Leverage} = \sum_i \frac{AUM_{i,t}}{\sum_i AUM_{i,t}} \times L_{i,t},$ where $AUM_{i,t}$ and $L_{i,t}$ refer to the aggregate AUM and leverage of the hedge fund company i in quarter t.
$\text{Exposure}^{\text{DLCT}}$	$Exposure^{DLCT}$ is the time-series loadings of each stock on the *DLCT* factor, estimated from a 12-month rolling regression of the stock's excess returns on market excess returns and the *DLCT* factor.
$\text{Exposure}^{\text{MF\_LCT}}$	$Exposure_{s,t}^{MF\ LTC}$ is the time-series loadings of each stock on the *MF_LCT* factor, estimated from a 12-month rolling regression of the stock's excess returns on market excess returns and the *MF_LCT* factor.
$\text{Exposure}^{\text{HF\_Leverage LCT}}$	$Exposure_{s,t}^{HF\ Leverage\ LTC}$ is the time-series loadings of each stock on the *HF Leverage LCT* factor, estimated from a 12-month rolling regression of the stock's excess returns on market excess returns and the *HF Leverage LCT* factor.
Market Equity	$Log(1 + Price_{s,t} \times Shrout_{s,t})$
Book-to-Market	$Log(1 + Book\ equity_{s,t}/Market\ equity_{s,t})$
Profits-to-Assets	$Prifits_{s,t}/TotalAssets_{s,t}$
Asset Growth	$\frac{TotalAssets_{s,t}}{TotalAssets_{s,t-1}} - 1$
Stock Return Run up	Stock returns during the 11-month period ending in $t - 1$
Reversals	Month t stock return
Idiosyncratic Volatility	Residual standard deviation from month-*t* three-factor model regression of daily returns

Table 1: Summary Statistics for Hedge Fund Companies

This table presents quarterly summary statistics for the hedge fund companies included in our study. Assets (Log) is the logarithm of the asset value reported by fund companies through 13F filings. AUM (Log) is the logarithm of assets under management (AUM) reported by the fund families to the data providers. Hedge fund return (HF Return) is quarterly return of the hedge fund company. After-fee returns are reported by hedge funds. We follow Agarwal, Daniel and Naik (2009) to estimate the before-fee returns from the reported after-fee returns. Dynamic fee is the difference between the before-fee and after-fee returns. Quarterly flows into the family (HF Flow) are computed by subtracting the previous quarter's AUM, adjusted by performance, from the end of quarter AUM and dividing by the previous quarter's AUM, adjusted by performance. N_Funds is the number of funds and N_Stocks the number of stocks reported in the 13F filings for the fund companies. Leverage refers to the asset-implied leverage, computed by dividing the value of the 13F reported assets by the AUM of each family. Active leverage change is the change in asset-implied leverage resulting from transactions and flows within the family, netting out the effect of performance. Holding beta represents the value-weighted beta of the stocks reported in the 13F filings. Active holding beta change is the change in holding beta resulting from the active action or discretionary investment decision of the family, netting out the effect of stock price changes.

Variables:	Mean	Std. Dev.	25%	50%	75%
Assets (Log)	19.93	1.90	18.72	19.69	20.95
AUM (Log)	19.82	1.78	18.68	19.73	20.76
HF Return (Before-fee)	1.73%	7.87%	-1.38%	1.71%	4.96%
HF Return (After-fee)	1.39%	7.36%	-1.31%	1.51%	4.34%
Dynamic Fee	0.35%	0.76%	0.00%	0.11%	0.54%
HF Flow	2.38%	22.68%	-4.58%	-0.06%	4.90%
N_Funds	4.93	9.36	1	3	5
N_Stocks	228.69	470.80	34	74	219
Leverage	3.44	5.10	0.50	1.22	3.72
Active Leverage Change	0.02	0.26	-0.08	0.00	0.11
Holding Beta	1.13	0.61	0.89	1.06	1.31
Active Holding Beta Change	-0.01	0.80	-0.22	0.00	0.21

Table 2: Hedge Fund Portfolios Sorted by Asset-Implied Leverage

This table reports portfolio characteristics of hedge fund companies sorted by their asset-implied leverage. We measure asset-implied leverage as the reported value of equity holdings from 13F filings, scaled by the corresponding assets under management (AUM) each quarter. Following Agarwal, Daniel and Naik (2009), we use monthly after-fee returns and characteristics of each hedge fund to estimate its monthly before-fee returns. The dynamic fees are the differences between the before-fee and after-fee returns of each fund. We aggregate the dynamic fees, before-fee returns, and after-fee returns at the fund company level each quarter. At the beginning of each quarter, we sort hedge fund companies into 5 quintiles, based on their asset-implied leverage during the previous quarter, and we calculate the equal-weighted average of quarterly dynamic fees and performance. Panel A presents averages of leverage, log-Asset holdings, log-AUM, Sharpe ratio and skewness of before-fee returns for hedge fund companies in each quintile. Panel B reports averages of dynamic fees, the risk-adjusted dynamic fees, the risk-adjusted before-fee returns and after-fee returns. All risk-adjustment is done by using the Fung and Hsieh's (2004) seven-factor model. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Leverage, Log-Asset, Log-AUM. Sharpe Ratio and Skewness

Portfolio Sorted by Leverage	Leverage	Log-Assets	Log-AUM	Sharpe Ratio (Before-Fee)	Skewness (Before-Fee)
1 (Low)	0.1804	18.8891	20.9672	0.1506	-0.3234
2	0.5624	19.5924	20.2110	0.1542	0.2110
3	1.1556	19.5896	19.4815	0.1829	0.1400
4	2.6598	20.4108	19.4985	0.1616	-0.3096
5 (High)	10.3663	21.2177	18.8848	0.2158	0.2363

Panel B: Dynamic fees, Risk-adjusted dynamic Fees, Before-fee and After-fee Returns

Portfolio Sorted by Leverage	Dynamic Fees (Quarterly, in %)		Before-Fee Return	After-Fee Return
	Unadjusted	7-Factor Adjusted	7-Factor Adjusted	7-Factor Adjusted
1 (Low)	0.3474***	0.3068***	0.6797***	0.3729*
	(9.60)	(11.49)	(3.13)	(1.86)
2	0.3603***	0.3033***	0.6131**	0.3098
	(8.28)	(9.35)	(2.34)	(1.32)
3	0.4089***	0.3454***	0.9047***	0.5594***
	(9.62)	(11.57)	(4.49)	(3.07)
4	0.4139***	0.3484***	0.7077***	0.3593**
	(8.30)	(9.96)	(3.56)	(2.03)
5 (High)	0.4912***	0.4115***	1.1339***	0.7224***
	(9.32)	(9.66)	(4.50)	(3.35)
High – Low	0.1438***	0.1047***	0.4541*	0.3494
	(4.01)	(3.14)	(1.91)	(1.66)

Table 3: The Effect of Asset-implied Leverage on Dynamic Fees

This table reports the results of regressing quarterly dynamic fees on asset-implied leverage. The panel regression model is

$$\text{Dynamic fee}_{i,t} = \alpha + \beta \times Leverage_{i,t-1} + \delta \times M_{i,t-1} + \epsilon_{i,t},$$

where $Dynamic\ fee_{i,t}$ denotes the dynamic fee (in %) of hedge fund company i in quarter t, which is calculated as the differences between the before-fee and after-fee returns; $Leverage_{i,t-1}$ represents the asset-implied leverage of hedge fund company i in quarter $t-1$, which is estimated as the value of asset holdings of each hedge fund company reported in 13F filings scaled by reported assets under management each quarter; and the vector $M_{i,t-1}$ includes a list of control variables in quarter $t-1$, including hedge funds returns, the value of asset holdings (log dollar), hedge fund flows, the number of funds in the company, as well as the number of stocks invested by the company. Columns (1) and (4) present results for the full sample; Columns (2) and (5) for a sub-sample of single-fund companies, while Columns (3) and (6) for a sub-sample of multi-fund companies. We include the hedge fund company (HF family) fixed effects and time (year-quarter) fixed effects in all specifications. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:	Quarterly Dynamic Fees Unadjusted (in %)			Quarterly Dynamic Fees 7-Factor Adjusted (in %)		
	Full Sample	Single-Fund Company	Multi-Fund Company	Full Sample	Single-Fund Company	Multi-Fund Company
	(1)	(2)	(3)	(4)	(5)	(6)
$Leverage_{t-1}$	0.0101***	0.0189***	0.0095***	0.0089***	0.0200***	0.0079**
	(3.54)	(2.81)	(2.64)	(3.30)	(3.18)	(2.33)
$HF\ Return_{t-1}$	1.0237***	0.9594***	0.9090***	0.6773***	0.6289**	0.6134***
	(6.20)	(3.05)	(4.98)	(4.87)	(2.23)	(4.04)
$Assets_{t-1}$	-0.0279***	-0.0437	-0.0214*	-0.0224**	-0.0418	-0.0178*
	(-2.73)	(-1.54)	(-1.93)	(-2.42)	(-1.60)	(-1.79)
$HF\ Flow_{t-1}$	0.0137	0.0114*	0.0118	0.0134	0.0077**	0.0130
	(0.88)	(1.95)	(0.55)	(0.87)	(2.19)	(0.61)
N_Funds_{t-1}	-0.0006			-0.0002		
	(-0.44)			(-0.19)		
N_Stocks_{t-1}	-0.0037	-0.0102	-0.0106	-0.0048	-0.0262	-0.0050
	(-0.21)	(-0.23)	(-0.54)	(-0.31)	(-0.67)	(-0.29)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11590	3084	8483	11590	3084	8483
adj. R-sq	0.232	0.227	0.243	0.188	0.187	0.197

Table 4: Leverage Policies vs. Lagged Returns

This table reports the results of regressing active leverage changes on lagged returns. The panel regression model is

$$\Delta L_{i.t} = \alpha + \beta \times HF\ return_{i,t-1} + \delta \times M_{i,t-1} + \epsilon_{i,t},$$

where $\Delta L_{i.t}$ denotes the active leverage change of hedge fund company i in quarter t; $HF\ return_{i,t-1}$ is the return of hedge fund company i over the previous quarter; $HF\ return_{i,t-1,SemiAnnual}$ represents the cumulative returns of hedge fund company i over the previous 6 months; and the vector $M_{i,t-1}$ includes a list of control variables in quarter $t-1$, including hedge funds returns, the value of asset holdings (log dollar), hedge fund flows, the number of funds in the company, as well as the number of stocks invested by the company. Columns (1) and (2) present results for the full sample; Columns (3) and (4) for a sub-sample of single-fund companies, while Columns (5) and (6) for a sub-sample of multi-fund companies. We include the hedge fund company (HF family) and time (year-quarter) fixed effects in all specifications. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Dependent Variable: Active Leverage Change $\Delta L_{i.t}$					
	Full Sample		Single-Fund Company		Multi-Fund Company	
	(1)	(2)	(3)	(4)	(5)	(6)
HF Return$_{t-1}$	0.1180***		0.1391***		0.1012***	
	(3.95)		(2.74)		(2.72)	
HF Return$_{t-1,SemiAnnual}$		0.0948***		0.1283***		0.0739***
		(4.90)		(3.53)		(3.00)
Assets$_{t-1}$	-0.0127***	-0.0128***	-0.0184**	-0.0185**	-0.0114***	-0.0115***
	(-3.76)	(-3.78)	(-2.21)	(-2.23)	(-2.96)	(-2.97)
HF Flow$_{t-1}$	0.0039***	0.0038***	0.0026*	0.0025*	0.0047***	0.0046***
	(2.96)	(2.93)	(1.88)	(1.89)	(2.79)	(2.76)
N_Funds$_{t-1}$	0.0004	0.0004				
	(0.70)	(0.74)				
N_Stocks$_{t-1}$	-0.0324***	-0.0322***	-0.0391***	-0.0383***	-0.0336***	-0.0335***
	(-5.10)	(-5.06)	(-2.88)	(-2.83)	(-4.31)	(-4.29)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13906	13906	3633	3633	10273	10273
adj. R-sq	0.163	0.163	0.116	0.118	0.190	0.190

Table 5: Investment Policies (Holding Betas) vs. Lagged Returns

This table reports the results of regressing the change in active holding beta on the lagged returns. The panel regression model is

$$\Delta HB_{i.t} = \alpha + \beta \times HF\ return_{i,t-1} + \delta \times M_{i,t-1} + \epsilon_{i,t}$$

where $\Delta HB_{i.t}$ denotes the change in active holding beta of hedge fund company i in quarter t; $HF\ return_{i,t-1}$ is the return of hedge fund company i over the previous quarter; $HF\ return_{i,t-1,SemiAnnual}$ is the cumulative returns of hedge fund company i over the previous 6 months; and the vector $M_{i,t-1}$ includes a list of control variables in quarter $t-1$, including hedge funds returns, the value of asset holdings (log dollar), hedge fund flows, the number of funds in the company, as well as the number of stocks invested by the company. Columns (1) and (2) present results for the full sample; Columns (3) and (4) for a sub-sample of single-fund companies, while Columns (5) and (6) for a sub-sample of multi-fund companies. We include the hedge fund company (HF family) fixed effects and time (year-quarter) fixed effects in all specifications. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable: Active Holding Beta Change ($\Delta HB_{i,t}$)						
	Full Sample		Single-Fund Company		Multi-Fund Company	
	(1)	(2)	(3)	(4)	(5)	(6)
HF Return$_{t-1}$	-0.2228**		-0.4350*		-0.0995	
	(-2.17)		(-1.95)		(-0.92)	
HF Return$_{t-1,SemiAnnual}$		-0.2017***		-0.2585**		-0.1604**
		(-3.01)		(-1.96)		(-1.99)
Assets$_{t-1}$	0.0012	0.0014	0.0393	0.0389	-0.0046	-0.0047
	(0.15)	(0.17)	(1.40)	(1.39)	(-0.60)	(-0.60)
HF Flow$_{t-1}$	-0.0025	-0.0023	0.0015	0.0016	-0.0058	-0.0055
	(-1.01)	(-0.95)	(0.63)	(0.66)	(-1.44)	(-1.38)
N_Funds$_{t-1}$	0.0001	0.0001				
	(0.08)	(0.04)				
N_Stocks$_{t-1}$	-0.0071	-0.0075	-0.0558	-0.0562	0.0103	0.0102
	(-0.39)	(-0.41)	(-1.18)	(-1.19)	(0.48)	(0.48)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13906	13906	3633	3633	10273	10273
adj. R-sq	0.056	0.056	0.042	0.041	0.071	0.072

Table 6: Simultaneous Adjustments in Leverage and Investment Policies

We construct dummy variables that correspond to four different scenarios: (1) I{ΔL<0, ΔHB>0}, an indicator variable that takes a value of one if a hedge fund company reduces leverage and increases holding betas simultaneously; (2) I{ΔL>0, ΔHB>0}, which indicates an increase in leverage and holding beta simultaneously; (3) I{ΔL>0, ΔHB<0}, which indicates an increase in leverage and a decrease in holding beta simultaneously; and (4) I{ΔL<0, ΔHB<0}, which indicates a decrease in leverage and holding beta simultaneously. The panel regression model is

$$D\{Simultanuous\ Change\}_{i.t} = \alpha + \beta \times HF\ return_{i,t-1,SemiAnnual} + \delta \times M_{i,t-1} + \epsilon_{i,t},$$

where $D\{Simultanuous\ Change\}_{i.t}$ denotes the four dummy variables in Columns (1) to (4), respectively; $HF\ Return_{i,t-1,SemiAnnual}$ refers to the cumulative returns of hedge fund company i over the previous 6 months. In our regressions, we decompose the lagged semi-annual returns into two signed components. The positive component is calculated as $HF\ return^{+} = HF\ return \times I\{HF\ return > 0\}$, where $I\{.\}$ is an indicator function, and the negative component is calculated as $HF\ return^{-} = HF\ return \times I\{HF\ return \leq 0\}$. In this way, we obtain the positive signed part ($HF\ return^{+}_{i,t-1,SemiAnnual}$) and the negative signed part ($HF\ return^{-}_{i,t-1,SemiAnnual}$) of the lagged semi-annual returns. The vector $M_{i,t-1}$ includes a list of control variables in quarter $t-1$, including hedge funds returns, the value of asset holdings (log dollar), hedge fund flows, the number of funds in the company, and the number of stocks invested by the company. Results in Panel A are based on the full sample of hedge fund companies, while results in Panel B (C) are based on the sub-sample of single-fund (multi-fund) companies. We include the hedge fund company (HF family) fixed effects and time (year-quarter) fixed effects in all specifications. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Regressions with the Full Sample

Dependent Variable:	I{ΔL<0, ΔHB>0}	I{ΔL>0, ΔHB>0}	I{ΔL>0, ΔHB<0}	I{ΔL<0, ΔHB<0}
	Full Sample			
	(1)	(2)	(3)	(4)
$HF\ Return^{+}_{t-1,SemiAnnual}$	0.0073	-0.0291	0.1048**	-0.0990
	(0.16)	(-0.70)	(2.26)	(-1.38)
$HF\ Return^{-}_{t-1,SemiAnnual}$	-0.3313***	0.0882	0.2934***	-0.0645
	(-3.48)	(1.01)	(3.43)	(-0.71)
$Assets_{t-1}$	0.0108**	-0.0064	-0.0109***	0.0063
	(2.50)	(-1.55)	(-2.81)	(1.38)
$HF\ Flow_{t-1}$	-0.0019	0.0024	0.0022	-0.0029
	(-0.69)	(0.76)	(0.72)	(-1.09)
N_Funds_{t-1}	0.0010	-0.0011	0.0004	-0.0002
	(0.85)	(-0.93)	(0.35)	(-0.19)
N_Stocks_{t-1}	0.0043	-0.0254***	-0.0039	0.0277***
	(0.48)	(-2.79)	(-0.43)	(2.93)
Time FE	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes
N	13906	13906	13906	13906
adj. R-sq	0.046	0.043	0.065	0.044

Panel B: Regressions with the Single-Fund HF Company Sub-sample

Dependent Variable:	I{ΔL<0, ΔHB>0}	I{ΔL>0, ΔHB>0}	I{ΔL>0, ΔHB<0}	I{ΔL<0, ΔHB<0}
	Single-Fund Company			
	(1)	(2)	(3)	(4)
HF $\text{Return}^{+}_{t-1,\text{SemiAnnual}}$	-0.1916**	0.0153	0.1915**	0.0272
	(-2.15)	(0.19)	(2.20)	(0.33)
HF $\text{Return}^{-}_{t-1,\text{SemiAnnual}}$	-0.2819*	0.1857	0.1967	-0.1509
	(-1.65)	(1.52)	(1.62)	(-1.18)
Assets_{t-1}	0.0504***	-0.0140*	-0.0107	0.0063
	(3.29)	(-1.75)	(-1.51)	(0.80)
HF Flow_{t-1}	-0.0022	0.0046	0.0043	-0.0044
	(-1.15)	(1.21)	(0.98)	(-1.00)
N_Stocks_{t-1}	-0.0163	-0.0417**	-0.0019	0.0282
	(-0.71)	(-2.25)	(-0.11)	(1.57)
Time FE	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes
N	3633	3633	3633	3633
adj. R-sq	0.040	0.035	0.054	0.018

Panel C: Regressions with the Multi-Fund HF Company Sub-sample

Dependent variable:	I{ΔL<0, ΔHB>0}	I{ΔL>0, ΔHB>0}	I{ΔL>0, ΔHB<0}	I{ΔL<0, ΔHB<0}
	Multi-Fund Company			
	(1)	(2)	(3)	(4)
HF $\text{Return}^{+}_{t-1,\text{SemiAnnual}}$	0.0850	-0.0523	0.0888	-0.1402
	(1.41)	(-1.08)	(1.58)	(-1.61)
HF $\text{Return}^{-}_{t-1,\text{SemiAnnual}}$	-0.3504***	0.0400	0.3142***	-0.0324
	(-3.02)	(0.36)	(2.91)	(-0.29)
Assets_{t-1}	0.0073	-0.0040	-0.0088**	0.0049
	(1.57)	(-0.89)	(-2.15)	(1.04)
HF Flow_{t-1}	-0.0006	0.0019	0.0017	-0.0035
	(-0.13)	(0.45)	(0.44)	(-0.96)
N_Stocks_{t-1}	0.0019	-0.0142	-0.0098	0.0254**
	(0.18)	(-1.38)	(-0.92)	(2.37)
Time FE	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes
N	10273	10273	10273	10273
adj. R-sq	0.051	0.044	0.069	0.051

Table 7: Performance of Stock Portfolios Sorted by Exposure to *DLCT* Factor

This table reports the average excess returns and alphas, in percent per month, for portfolios of stocks sorted by their exposure to the *DLCT* factor. For each stock, we obtain a time-series of loadings ($Exposure^{DLCT}$) of the stock on the hedge fund *DLCT* (the delegated leverage constraint tightness) factor, estimated using rolling-window regressions of the stock's excess returns on market excess returns and the *DLCT* factor. The *DLCT* factor is the innovations in the variable *DLCT* from an AR (1) model. We use the aggregate holdings of single-fund hedge fund companies to construct *DLCT* factor. Stocks are assigned into groups at the end of month t, and portfolios are held during month t + 1. We report results of average excess returns and alphas using the CAPM model, the Fama-French (1993) 3-factor model, the Carhart (1997) 4-factor model and the Pastor-Stambaugh (2003) 5-factor model. The Newey and West (1987) T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Portfolio Sorted by	Excess Return	Alphas from factor models			
$Exposure^{DLCT}$	(Monthly, in %)	CAPM	3-Factor	4-Factor	5-Factor
1 (Low)	0.9403	0.0620	0.0686	0.1091	0.1090
2	0.8385	0.1608	0.1451	0.1335	0.1335
3	0.7018	0.0840	0.0751	0.0673	0.0668
4	0.5835	-0.1041	-0.1055	-0.0973	-0.0964
5 (High)	0.3582	-0.5251	-0.4900	-0.4323	-0.4314
Low – High	0.5821**	0.5871**	0.5586**	0.5414**	0.5404**
	(2.45)	(2.44)	(2.34)	(2.24)	(2.23)

Table 8: Fama-MacBeth Regressions of Monthly Stock Returns on Exposure to the *DLC*T Factor

This table reports the results of Fama-MacBeth regressions of monthly stock returns on their exposures to the hedge fund *DLCT* (the delegated leverage constraint tightness) factor. Stock returns (in percent) in month $t + 1$ are regressed on *Exposure*^{DLCT} computed as of month t, which is the stock's exposure to the *DLCT* factor. The variable *DLCT* is the aggregate hedge fund beta, estimated by using the value-weighted hedge fund holding betas. The *DLCT* factor is the innovations in the variable *DLCT* from an AR (1) model. We use the aggregate holdings of single-fund companies to construct *DLCT*. Other independent variables include the stock's market equity, book-to-market ratio, profits-to-assets ratio, asset growth rate, stock return run up, reversals, and idiosyncratic volatility in month *t*. All independent variables are normalized to have a cross-sectional standard deviation of one and are defined in Appendix A. Reported are the average coefficients and Newey and West (1987) T-statistics (in parentheses). Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:	Stock Return$_{t+1}$ (Monthly, in %)					
	Specifications					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$^{DLCT}_t$	-0.1869***	-0.1689***	-0.1651***	-0.1890***	-0.1174***	-0.0937**
	(-3.41)	(-3.33)	(-3.29)	(-3.49)	(-2.83)	(-2.48)
Market Equity$_t$		-0.1923	-0.1976*	-0.2090*	-0.1638	-0.1767**
		(-1.61)	(-1.66)	(-1.77)	(-1.47)	(-2.16)
Book to Market Ratio$_t$		0.2061**	0.2182**	0.1652*	0.1969**	0.1882**
		(2.25)	(2.37)	(1.88)	(2.33)	(2.43)
Profits_to_Assets$_t$			0.5246**	0.4949**	0.5120**	0.4986**
			(2.43)	(2.27)	(2.33)	(2.37)
Asset_Growth$_t$				-0.3663***	-0.4438***	-0.4352***
				(-3.43)	(-4.06)	(-4.03)
Stock Return Run Up$_t$					0.0403	0.0655
					(0.35)	(0.61)
Reversals$_t$					-0.5314***	-0.5453***
					(-5.98)	(-6.02)
Idiosyncratic Volatility$_t$						-0.0372
						(-0.27)

Table 9: Fama-MacBeth Regressions of Monthly Stock Returns on Exposure to the *DLCT* Factor: Additional Specifications

This table reports the results of Fama-MacBeth regressions of monthly stock returns on their exposures to the hedge fund *DLCT* (the delegated leverage constraint tightness) factor with additional specifications. Stock returns (in percent) in month $t+1$ are regressed on $Exposure^{DLCT}$ computed as of month t, which is the stock's exposure to the *DLCT* factor. The variable *DLCT* is the aggregate hedge fund beta, estimated by the value-weighted hedge fund holding betas. The *DLCT* factor is the innovations in the variable *DLCT* from an AR (1) model. We use the aggregate holdings of single-fund hedge fund companies to construct *DLCT*. In Column (1), we exclude all the penny stocks in our sample. In Column (2), we further control for $Exposure^{MF\_LCT}$, which is the stock's exposure to the mutual fund LCT factor (Boguth and Simutin 2018). In Columns (3) and (4), we further divide our sample period into two subperiods: one characterized by reduced hedge fund leverage (below-medium innovations) and the other by enhanced hedge fund leverage (above-medium innovations). Other independent variables include the stock's market equity, book-to-market ratio, profits-to-assets ratio, asset growth rate, stock return run up, reversals, and idiosyncratic volatility in month t. All independent variables are normalized to have a cross-sectional standard deviation of one. Reported are the average coefficients and Newey and West (1987) T-statistics (in parentheses). Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:	Stock Return$_{t+1}$ (Monthly, in %)			
	Dropping Penny Stocks	Controlling for Mutual Fund LCT	Subperiods by Implied Leverage Innovations	
			Below Medium	Above Medium
	(1)	(2)	(3)	(4)
$Exposure^{DLCT}_t$	-0.0883**	-0.1082**	-0.1101**	-0.0660
	(-2.46)	(-2.00)	(-2.14)	(-1.46)
$Exposure^{MF\_LCT}_t$		-0.0916		
		(-1.30)		
Market Equity$_t$	-0.1248*	-0.1408*	-0.1298	-0.1198
	(-1.73)	(-1.94)	(-1.35)	(-1.00)
Book to Market Ratio$_t$	0.2000**	0.1947**	0.2196**	0.1799
	(2.58)	(2.52)	(2.02)	(1.53)
Profits_to_Assets$_t$	0.5267**	0.5247**	0.5203	0.5332**
	(2.51)	(2.53)	(1.50)	(2.03)
Asset_Growth$_t$	-0.3999***	-0.3976***	-0.3742***	-0.4261***
	(-3.82)	(-3.79)	(-2.82)	(-3.08)
Stock Return Run Up$_t$	0.1084	0.1090	-0.0121	0.2313**
	(1.13)	(1.14)	(-0.07)	(2.33)
Reversals$_t$	-0.3072***	-0.3137***	-0.3564***	-0.2569***
	(-4.42)	(-4.29)	(-2.77)	(-2.81)
Idiosyncratic Volatility$_t$	-0.3591**	-0.3437**	-0.4820**	-0.2337
	(-2.45)	(-2.36)	(-2.05)	(-1.17)

Table 10: Exposures to *DLCT* Factor and Lehman HF Holdings

This table presents results of regressing the change in stocks' exposures to the hedge fund *DLCT* factor on holdings by Lehman-connected hedge funds. We estimate the following panel regression model:

$$\begin{aligned}\Delta Exposure_{i,t}^{DLTC} &= \alpha + \beta_1 \times Lehman\ HF\ holdings_{i,2008.06} \\ &+ \beta_2 \times Non_{Lehman} HF\ holdings_{i,2008.06} + \beta_3 \times MF\ holdings_{i,2008.06} \\ &+ \beta_4 \times Other\ Institutional\ holdings_{i,2008.06} + \epsilon_{i,t},\end{aligned}$$

where $\Delta Exposure^{DCLP\ beta}{}_{i,t}$ denotes the change in the exposure of stock i to the *DLCT* factor in month t. The variable *DLCT* is the aggregate hedge fund beta, estimated by using the value-weighted hedge fund holding betas. The *DLCT* factor is the innovations in the variable *DLCT* from an AR (1) model. We use the aggregate holdings of single-fund hedge fund companies to construct the *DLCT* factor. $Lehman\ HF\ holdings_{i,2008.06}$ refers to the percentage of shares held by Lehman-connected hedge funds in June 2008, as defined in Aragon and Strahan (2012). We also include the percentage of shares held by non-Lehman-connected hedge funds (Non-Lehman HF holdings), shares held by mutual funds, and by other non-MF and non-MF institutions (Other-institutions holdings) in June 2008. In Columns (1)-(3), the dependent variables are changes in stock's exposure to the hedge fund DLCT factor for the three time periods, 2008/01-2008/04, 2008/05-2008/08 and 2008/09-2008/12. The first two periods are prior to the Lehman bankruptcy and the last one is during the Lehman bankruptcy. In Column (4), the dependent variable is the change in stock's exposures to the mutual fund *LCT* factor in the time period of 2008/09-2008/12. We include time (year-month) fixed effects in all specifications. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:		ΔExposure^{DLCT}		ΔExposure^{MF_LCT}
	[2008.01, 2008.04]	[2008.05, 2008.08]	[2008.09, 2008.12]	[2008.09, 2008.12]
	(1)	(2)	(3)	(4)
Lehman HF Holdings$_{2008.06}$	0.0433	0.1201	0.2667***	-0.0813
	(0.35)	(0.99)	(3.21)	(-1.16)
Non-Lehman HF Holdings$_{2008.06}$	-0.0301	-0.0392	0.0104	0.0134
	(-0.99)	(-1.39)	(0.61)	(0.76)
MF Holdings$_{2008.06}$	0.0229	-0.0124	-0.0588***	0.0260**
	(1.19)	(-0.67)	(-4.96)	(2.35)
Other-Institutions Holdings$_{2008.06}$	0.0161	-0.0277	-0.0582***	0.0005
	(0.79)	(-1.42)	(-4.80)	(0.05)
Time FE	Yes	Yes	Yes	Yes
N	23365	23895	23702	23702
adj. R-sq	0.001	0.012	0.025	0.004

<u>Online Appendix</u>

Delegated Leverage and Asset Prices: Evidence from the Hedge Fund Industry

This Online Appendix consists of two parts. Part 1 presents the proof of the model. Part 2 tabulates the results of a list of additional empirical analyses discussed in the main text.

Part 1: Appendix for the Proofs of the Model

Proof (Lemma 1): The optimal demand can be written as

$$\boldsymbol{\theta}_k = \frac{1}{\gamma_k}\boldsymbol{\Sigma}^{-1}(\mathbb{E}[\boldsymbol{R}_e] - \phi_k \mathbb{1}) \tag{A1}$$

where $\phi_k \geq 0$ is the Lagrange multiplier on leverage constraint as stated in Eq. (1). Next, we can derive from the market-clearing condition the market portfolio weight under investors' optimal investment policies: $\boldsymbol{X}^R = \sum_{k=1}^{K} \frac{W_k}{W^R}\boldsymbol{\theta}_k$. Applying (A1) to it, we have $\boldsymbol{X}^R = \sum_k \frac{W_k}{\gamma W^R}\boldsymbol{\Sigma}^{-1}(\mathbb{E}[\boldsymbol{R}_e] - \phi_k \mathbb{1}) = \frac{1}{\theta^R \gamma}\boldsymbol{\Sigma}^{-1}(\mathbb{E}[\boldsymbol{R}_e] - \phi_k \mathbb{1})$. Denoting $\gamma^R = \theta^R\gamma$, we have:

$$\boldsymbol{X}^R = \frac{1}{\gamma^R}\boldsymbol{\Sigma}^{-1}(\mathbb{E}[\boldsymbol{R}_e] - \psi \mathbb{1}). \tag{A2}$$

Eq. (A2) describes the market portfolio of the economy, from which we further get:

$$\mathbb{E}[\boldsymbol{R}_e] = \gamma^R \boldsymbol{\Sigma}\boldsymbol{X}^R + \psi\mathbb{1}. \tag{A3}$$

It is noted that $\boldsymbol{\Sigma}\boldsymbol{X}^R = \mathrm{cov}(\boldsymbol{R}_e, R_{MKT})$, we have:

$$\mathbb{E}[\boldsymbol{R}_e] = \gamma^R \mathrm{cov}(\boldsymbol{R}_e, R_{MKT}) + \psi\mathbb{1}. \tag{A4}$$

Since $\mathbb{E}[R_{mkt}] = (\boldsymbol{X}^R)'\mathbb{E}[\boldsymbol{R}_e]$, we can multiply the transpose of $\boldsymbol{X}^R$ on both sides of (A4) to derive the condition for the market portfolio. We have:

$$\mathbb{E}[R_{mkt}] = \gamma^R \boldsymbol{X}^{R'}\boldsymbol{\Sigma}\boldsymbol{X}^R + \psi = \gamma^R var(R_{MKT}) + \psi. \tag{A5}$$

Plugging this expression back into (A4), we get Eq. (6). ■

Proof (Proposition 1): We can rewrite investors' optimal investment policy (A1) as the part related to market portfolio (A2) and a tilting portfolio as follows:

$$\begin{aligned}
\boldsymbol{\theta}_k &= \frac{1}{\gamma}\boldsymbol{\Sigma}^{-1}(\mathbb{E}[\boldsymbol{R}_e] - \phi_k \mathbb{1}) \\
&= \frac{1}{\gamma}\boldsymbol{\Sigma}^{-1}(\mathbb{E}[\boldsymbol{R}_e] - \psi\mathbb{1} - (\phi_k - \psi)\mathbb{1}) \\
&= \frac{\gamma^R}{\gamma}\boldsymbol{X}^R + \frac{(\psi - \phi_k)}{\gamma}\boldsymbol{\Sigma}^{-1}\mathbb{1} \\
&= \theta^R\boldsymbol{X}^R + \frac{(\psi - \phi_k)}{\gamma}\boldsymbol{\Sigma}^{-1}\mathbb{1}.
\end{aligned} \tag{A6}$$

Based on Eq. (A6), we can further write down the expected returns of an investor as (by multiplying the transpose of both sides of A6 to $\mathbb{E}[\boldsymbol{R}_e]$):

$$\bar{r}_k = \mathbb{E}[\boldsymbol{\theta}_k' \boldsymbol{R}_e] = \theta^R (\boldsymbol{X}^R)' \mathbb{E}[\boldsymbol{R}_e] + \frac{(\psi - \phi_k)}{\gamma} \mathbb{I}' \boldsymbol{\Sigma}^{-1} \boldsymbol{R}_e$$

$$= \theta^R \mathbb{E}[R_{mkt}] + \frac{(\psi - \phi_k)}{\gamma} \mathbb{I}' \boldsymbol{\Sigma}^{-1} \boldsymbol{R}_e, \quad \text{(A7)}$$

where in the last line we have plugged in the market return $\mathbb{E}[R_{mkt}] = (\boldsymbol{X}^R)' \mathbb{E}[\boldsymbol{R}_e]$. Next, multiplying $\mathbb{I}'$ to both sizes of (A6) and noticing that $\mathbb{I}' \boldsymbol{X}^R = 1$ for the market portfolio, we have

$$\theta_k^R = \mathbb{I}' \boldsymbol{\theta}_k = \theta^R + \frac{(\psi - \phi_k)}{\gamma} \mathbb{I}' \boldsymbol{\Sigma}^{-1} \mathbb{I}. \quad \text{(A8)}$$

Plugging (A8) into (A7) to replace $(\psi - \phi_k)/\gamma$, we have:

$$\bar{r}_k = \theta^R \mathbb{E}[R_{mkt}] + \rho \times (\theta_k^R - \theta^R), \quad \text{(A9)}$$

where the parameter $\rho = \frac{\mathbb{I}' \boldsymbol{\Sigma}^{-1} \boldsymbol{R}_e}{\mathbb{I}' \boldsymbol{\Sigma}^{-1} \mathbb{I}}$ is a scalar that synchronizes the marginal leverage benefit from the security market. Eq. (A9) suggests that the expected returns of hedge funds and long-only investors satisfy the following relationship:

$$\bar{r}_h = \bar{r}_l + B \times \left(\theta_h^R - \theta_l^R\right) = \bar{r}_l + \rho \times (m_h - 1). \quad \text{(A10)}$$

The second half of (A10) plugs in the binding leverage conditions of the hedge fund (i.e., $\theta_h^R = m_h$) and the long-only investor (i.e., $\theta_l^R = 1$). Rearranging terms proves the first property of Proposition 2.

To prove the second property, we notice that the BG condition (5) now becomes $\rho(m_h - 1) - f - bW_h - \frac{1}{2} c m_h^2 = 0$, from which we can drive fund AUM under the fee and leverage policies as:

$$W_h = \frac{1}{b}\left(\rho(m_h - 1) - \frac{1}{2} c m_h^2 - f\right). \quad \text{(A11)}$$

Hence, the manager's problem becomes:

$$Max_{f, m_h} \ \ U_{mgr} = \frac{1}{b} \times f \times \left(\rho(m_h - 1) - \frac{1}{2} c m_h^2 - f\right), \quad \text{(A12)}$$

which can be solved as follows. First, conditioning on fund leverage, optimal fund fee can be solved from the FOC (i.e., $\frac{\partial U_{mgr}}{\partial f} = 0$) as $f^* = \rho(m_h - 1) - \frac{1}{2} c m_h^2$. Plugging f^* into (A12), the manager maximizes $U_{mgr}(m_h, f^*) = \frac{1}{4b}\left(\rho(m_h - 1) - \frac{1}{2} c m_h^2\right)^2$. Its FOC gives out $m_h^* = \rho / c = \frac{1}{c} \times \frac{\mathbb{I}' \boldsymbol{\Sigma}^{-1} \boldsymbol{R}_e}{\mathbb{I}' \boldsymbol{\Sigma}^{-1} \mathbb{I}}$. Hence, $f^* = \frac{1}{2}\left(\frac{\rho^2}{2c} - \rho\right)$ and $W_h = \frac{1}{2b}\left(\frac{\rho^2}{2c} - \rho\right)$. When $\frac{1}{2b}\left(\frac{\rho^2}{2c} - \rho\right) < W$, the hedge fund can attract the optimal amount of capital based on its optimal fee and leverage strategy. ■

Proof (Proposition 2): From Proposition 1 and Equation (8), it is trivial that a declining marginal benefit of leverage or a hiking funding cost tightens hedge fund leverage (i.e., leading to smaller m_h). We mainly focus on the second part of the proposition. Here, we want to prove that m_h is negatively correlated with hedge fund beta as well as the tightness of capital constraints (i.e., ϕ_h). Hence, adverse funding shocks reducing the value of m_h will increase hedge fund beta and the level of ϕ_h.

From (A6), we have that the levered portfolio beta satisfies:

$$\beta_h = \theta^R \boldsymbol{\beta}' \boldsymbol{X}^R + \frac{(\psi-\phi_h)}{\gamma} \boldsymbol{\beta}' \boldsymbol{\Sigma}^{-1} \mathbb{1} = \theta^R + \frac{(\psi-\phi_h)}{\gamma} \boldsymbol{\beta}' \boldsymbol{\Sigma}^{-1} \mathbb{1}, \tag{A13}$$

where we have used the property that the market portfolio has a holding beta of one ($\boldsymbol{\beta}' \boldsymbol{X}^R = \mathbf{1}$). Next, Eq. (A8) implies that

$$\frac{(\psi-\phi_h)}{\gamma} = \frac{\theta_h^R - \theta^R}{\mathbb{1}' \boldsymbol{\Sigma}^{-1} \mathbb{1}}, \tag{A14}$$

and, by plugging (A14) into (A13),

$$\beta_h = \theta^R + \frac{\boldsymbol{\beta}' \boldsymbol{\Sigma}^{-1} \mathbb{1}}{\mathbb{1}' \boldsymbol{\Sigma}^{-1} \mathbb{1}} \left(\theta_h^R - \theta^R\right). \tag{A15}$$

Dividing both sides of (A15) by θ_h^R, we have:

$$\bar{\beta}_h = \frac{\boldsymbol{\beta}' \boldsymbol{\Sigma}^{-1} \mathbb{1}}{\mathbb{1}' \boldsymbol{\Sigma}^{-1} \mathbb{1}} + \frac{\theta^R}{\theta_h^R} \left(1 - \frac{\boldsymbol{\beta}' \boldsymbol{\Sigma}^{-1} \mathbb{1}}{\mathbb{1}' \boldsymbol{\Sigma}^{-1} \mathbb{1}}\right). \tag{A16}$$

In (A16), the first part is a constant. The second part is positively related to $\frac{\theta^R}{\theta_h^R}$ when $\mathbb{1}' \boldsymbol{\Sigma}^{-1} \mathbb{1} > \boldsymbol{\beta}' \boldsymbol{\Sigma}^{-1} \mathbb{1}$. The latter condition holds under reasonable distributions of asset betas (e.g., when asset betas are symmetrically distributed around one). To see this point, we can rewrite Eq. (6) in realized asset returns as $\boldsymbol{R}_e = \boldsymbol{\beta}(R_{mkt} - \psi) + \psi \mathbb{1} + \boldsymbol{e}$, where $\boldsymbol{e}$ is the vector of idiosyncratic risk of stock returns. In this case,

$$\boldsymbol{\Sigma} = \boldsymbol{\beta} \boldsymbol{\beta}' \sigma_m^2 + \boldsymbol{\Sigma}_{\mathbf{e}}, \tag{A17}$$

where $\boldsymbol{\Sigma}_{\mathbf{e}}$ is the variance-covariance matrix of idiosyncratic risk. Assume that $\boldsymbol{\Sigma}_{\mathbf{e}}$ only has non-zero diagonal elements, which is the same for each asset (i.e., $\boldsymbol{\Sigma}_{\mathbf{e}} = \begin{pmatrix} e & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & e \end{pmatrix}$; hence $\boldsymbol{\Sigma}_{\mathbf{e}}^{-1}$ also has non-zero diagonal elements that equal to e^{-1}).[1] Applying the Sherman-Morrison formula to (A17), we have $\boldsymbol{\Sigma}^{-1} = \boldsymbol{\Sigma}_{\mathbf{e}}^{-1} - \frac{\boldsymbol{\Sigma}_{\mathbf{e}}^{-1} \boldsymbol{\beta} \boldsymbol{\beta}' \boldsymbol{\Sigma}_{\mathbf{e}}^{-1}}{\sigma_m^2 + \boldsymbol{\beta}' \boldsymbol{\Sigma}_{\mathbf{e}}^{-1} \boldsymbol{\beta}}$. Hence,

---

[1] This assumption can be relaxed. The condition holds as long as $\left(\boldsymbol{\Sigma}_{\mathbf{e}}^{-1}\right)_{ii} = \left(\boldsymbol{\Sigma}_{\mathbf{e}}^{-1}\right)_{jj} > \left(\boldsymbol{\Sigma}_{\mathbf{e}}^{-1}\right)_{ij} = \left(\boldsymbol{\Sigma}_{\mathbf{e}}^{-1}\right)_{ji}$, where the subscripts ij refers to the i-th row and j-th column element of $\boldsymbol{\Sigma}_{\mathbf{e}}^{-1}$. In this case, when $\beta_i > \beta_j$, $\left(\boldsymbol{\Sigma}_{\mathbf{e}}^{-1} \boldsymbol{\beta}\right)_{\boldsymbol{i}} > \left(\boldsymbol{\Sigma}_{\mathbf{e}}^{-1} \boldsymbol{\beta}\right)_{\boldsymbol{j}}$, because $\left(\boldsymbol{\Sigma}_{\mathbf{e}}^{-1} \boldsymbol{\beta}\right)_{\boldsymbol{i}} -$

$$\mathbf{\Sigma}^{-1}\mathbb{1} = \mathbf{\Sigma}_{\mathbf{e}}^{-1}\mathbb{1} - \frac{\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\mathbb{1}}{\sigma_m^2+\boldsymbol{\beta}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta}} = \mathbf{\Sigma}_{\mathbf{e}}^{-1}\mathbb{1} - \left(\frac{\boldsymbol{\beta}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\mathbb{1}}{\sigma_m^2+\boldsymbol{\beta}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta}}\right) \times \mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta} = \mathbf{\Sigma}_{\mathbf{e}}^{-1}\mathbb{1} - \eta\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta} \tag{A18}$$

Importantly, $\eta = \frac{\boldsymbol{\beta}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\mathbb{1}}{\sigma_m^2+\boldsymbol{\beta}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta}}$ is a scalar. From (A18), $\mathbb{1}'\mathbf{\Sigma}^{-1}\mathbb{1} = \frac{N}{e} - \frac{\eta}{e}\mathbb{1}'\boldsymbol{\beta}$ and $\boldsymbol{\beta}'\mathbf{\Sigma}^{-1}\mathbb{1} = \frac{N}{e} - \frac{\eta}{e}\boldsymbol{\beta}'\boldsymbol{\beta}$ (we have used the properties that $\mathbb{1}'\mathbb{1} = N$ and $\boldsymbol{\beta}'\mathbb{1} = N$). Easy to see, the condition $\mathbb{1}'\mathbf{\Sigma}^{-1}\mathbb{1} > \boldsymbol{\beta}'\mathbf{\Sigma}^{-1}\mathbb{1}$ holds as long as $\boldsymbol{\beta}'\boldsymbol{\beta} > \mathbb{1}'\boldsymbol{\beta}$. The latter condition holds under reasonable distributions of asset betas. For instance, when betas are symmetrically distributed around one, the latter condition holds because of Jensen's inequality. Hence, $\bar{\beta}_h$ is positively related to $\frac{\theta^R}{\theta_h^R}$ under these reasonable assumptions.

We now get back to (A16). Noticing that $\theta^R = \frac{W_h\theta_h^R + W_l\theta_l^R}{W_h+W_l}$, $\theta_l^R = 1$, and $\theta_h^R = m_h$, we have:

$$\frac{\theta^R}{\theta_h^R} = 1 + \frac{W_l}{W}\frac{\theta_l^R}{\theta_h^R} = 1 + \frac{W_l}{W}\frac{1}{m_h}. \tag{A19}$$

Since both W_l and $\frac{1}{m_h}$ decreases in m_h, $\frac{\theta^R}{\theta_h^R}$ and $\bar{\beta}_h$ are decreasing functions of m_h. This proves the negative leverage-beta relationship.

Finally, we examine how hedge fund's leverage policy is related to the tightness of capital constraints. From (A8), we have:

$$\theta_h^R - \theta^R = \frac{(\psi-\phi_k)}{\gamma}\mathbb{1}'\mathbf{\Sigma}^{-1}\mathbb{1}. \tag{A20}$$

Since $\theta^R = \frac{W_h\theta_h^R + W_l\theta_l^R}{W_h+W_l}$ and $\psi = \frac{W_h\phi_h + W_l\phi_l}{W_h+W_l}$, we have:

$$\theta_h^R - \theta^R = \frac{W_l(\theta_h^R - \theta_l^R)}{W_h+W_l}, \tag{A21}$$

$$\text{and } \psi - \phi_h = \frac{W_l(\phi_l - \phi_h)}{W_h+W_l}. \tag{A22}$$

Hence,

$$\theta_h^R - \theta_l^R = (\phi_l - \phi_h)\mathbb{1}'\mathbf{\Sigma}^{-1}\mathbb{1}, \tag{A23}$$

$(\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta})_j = (\mathbf{\Sigma}_{\mathbf{e}}^{-1})_{ii}\beta_i + (\mathbf{\Sigma}_{\mathbf{e}}^{-1})_{ij}\beta_j - \{(\mathbf{\Sigma}_{\mathbf{e}}^{-1})_{ji}\beta_i + (\mathbf{\Sigma}_{\mathbf{e}}^{-1})_{jj}\beta_j\} = ((\mathbf{\Sigma}_{\mathbf{e}}^{-1})_{ii} - (\mathbf{\Sigma}_{\mathbf{e}}^{-1})_{ij}) \times (\beta_i - \beta_j) > 0$. When betas are symmetrically distributed around one, we can examine a pair of betas such that $\beta_i = 1 + b$ and $\beta_j = 1 - b$. Jensen's inequality implies that $\beta_i(\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta})_i + \beta_j(\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta})_j > (\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta})_i + (\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta})_j$. Summing up all possible beta pairs leads to $\boldsymbol{\beta}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta} > \mathbb{1}'\mathbf{\Sigma}_{\mathbf{e}}^{-1}\boldsymbol{\beta}$ and thus, due to (A18), $\mathbb{1}'\mathbf{\Sigma}^{-1}\mathbb{1} > \boldsymbol{\beta}'\mathbf{\Sigma}^{-1}\mathbb{1}$.

which implies $m_h = (\phi_l - \phi_h)\mathbb{I}'\boldsymbol{\Sigma}^{-\mathbf{1}}\mathbb{I} + 1$ when $\theta_l^R = 1$ and $\theta_h^R = m_h$. It is easy to see that m_h and ϕ_h are negatively related (i.e., $\frac{\partial \phi_h}{\partial m_h} < 0$). ■

Part 2: Additional Tables

Table IN1: Dynamic Fees and Transition Matrix of HF Portfolios Sorted by Leverage

Panel A reports value-weighted dynamic fees of hedge fund company portfolios sorted by their asset-implied leverage. Panel B reports the transition matrix of hedge fund companies, where the transition from i to j represents the probability that a hedge fund family classified into quintile i in the current quarter is classified into quintile j in the next quarter. Asset-implied leverage is the value of equity holdings of each hedge fund company, as reported in 13F filings, scaled by assets under management in each quarter, Following Agarwal, Daniel and Naik (2009), we use the monthly after-fee returns and characteristics of hedge funds to back out the monthly before-fee returns. Dynamic fees are the differences between the before-fee and after-fee returns for each fund. We aggregate the dynamic fees, the before-fee returns and after-fee returns of each fund to the fund company level each quarter. At the beginning of each quarter, we sort hedge fund companies into 5 quintiles, based on their level of asset-implied leverage during the past quarter, and we calculate the value-weighted average of dynamic fees and quarterly returns for hedge fund companies in each quintile. We present unadjusted dynamic fees, and risk-adjusted dynamic fees by using the CAPM model, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Pastor-Stambaugh (2003) five-factor model, and the Fung and Hsieh's (2004) seven-factor model. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Value-Weighted Dynamic Fees

Portfolio Sorted by	Dynamic Fees (Quarterly, in %)					
Leverage	Unadjusted	1-Factor Adjusted	3-Factor Adjusted	4-Factor Adjusted	5-Factor Adjusted	7-Factor Adjusted
1 (Low)	0.3486	0.3268	0.3346	0.3189	0.3202	0.3079
	(9.44)	(10.18)	(10.97)	(11.08)	(11.14)	(11.23)
2	0.3584	0.3044	0.3046	0.2881	0.2893	0.3011
	(8.21)	(8.71)	(9.66)	(9.70)	(9.76)	(9.27)
3	0.4075	0.3525	0.3523	0.3399	0.3392	0.3445
	(9.57)	(10.58)	(11.42)	(11.38)	(11.43)	(11.54)
4	0.4137	0.3581	0.3604	0.3402	0.3393	0.3478
	(8.19)	(9.13)	(9.22)	(9.53)	(9.52)	(9.86)
5 (High)	0.4877	0.4258	0.4246	0.3995	0.4006	0.4093
	(9.17)	(9.30)	(9.55)	(9.89)	(9.93)	(9.43)
High – Low	0.1390***	0.0990**	0.0900**	0.0806**	0.0804**	0.1014***
	(3.77)	(2.65)	(2.36)	(2.28)	(2.27)	(2.94)

Panel B: Transition matrix

HF Company Sorted	Transition Rates of HF Company across Quintiles (%)				
by Leverage	1	2	3	4	5
1 (Low)	85.61	12.32	1.54	0.31	0.22
2	12.40	73.04	13.28	1.28	0.00
3	1.09	12.89	72.57	12.80	0.65
4	0.40	1.49	12.12	76.46	9.53
5 (High)	0.18	0.40	0.72	9.21	89.49

Table IN2: Hedge Fund Portfolios Sorted by Asset-Implied Leverage: Excluding AUMs of Fixed-income Oriented Funds

This table reports the average dynamic fees of hedge fund company portfolios sorted by their asset-implied leverage, excluding the AUM of fixed-income oriented funds. Asset-implied leverage is the value of equity holdings of each hedge fund company, as reported in 13F filings, scaled by assets under management in each quarter, In Columns (1) and (2), AUM sub-sample 1 uses the total AUM of all hedge funds within each company, excluding "Convertible Arbitrage", "Fixed Income Arbitrage" and "Managed Futures" funds. In Columns (3) and (4), AUM sub-sample 2 includes the total AUM of all hedge funds withing each company, excluding "Convertible Arbitrage", "Fixed Income Arbitrage", "Managed Futures", "Global Macro", "Options Strategy" and "Fund of Funds" funds. In Columns (5) and (6), AUM sub-sample 3 uses the total AUM of "Long/Short Equity Hedge" funds within each company. Following Agarwal, Daniel and Naik (2009), we use the monthly after-fee returns and characteristics of hedge funds to estimate the monthly before-fee returns. Dynamic fees are the differences between the before-fee and after-fee returns for each fund. We aggregate the dynamic fees, the before-fee returns and after-fee returns of each fund to the fund company level each quarter. At the beginning of each quarter, we sort hedge fund companies into 5 quintiles, based on their level of asset-implied leverage during the past quarter. We present value-weighted average of dynamic fees, and the Fung and Hsieh (2004) seven-factor adjusted dynamic fees for each quintile. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Portfolio Sorted by Leverage	Dynamic Fees (Quarterly, in %)					
	Average Fee	7-Factor Adjusted	Average Fee	7-Factor Adjusted	Average Fee	7-Factor Adjusted
	AUM Sub-Sample 1		AUM Sub-Sample 2		AUM Sub-Sample 3	
	(1)	(2)	(3)	(4)	(5)	(6)
1 (Low)	0.3482***	0.2994***	0.3499***	0.2975***	0.3513***	0.2986***
	(7.34)	(8.92)	(7.38)	(8.91)	(7.40)	(8.92)
2	0.4057***	0.3392***	0.4009***	0.3414***	0.4002***	0.3405***
	(8.32)	(9.37)	(8.15)	(9.35)	(8.14)	(9.34)
3	0.3955***	0.3338***	0.3975***	0.3343***	0.4028***	0.3400***
	(9.91)	(12.36)	(9.66)	(12.07)	(9.83)	(12.38)
4	0.4320***	0.3584***	0.4335***	0.3571***	0.4298***	0.3531***
	(7.94)	(9.29)	(8.19)	(9.66)	(8.14)	(9.58)
5 (High)	0.4823***	0.4099***	0.4797***	0.4081***	0.4832***	0.4113***
	(8.55)	(8.88)	(8.30)	(8.51)	(8.35)	(8.58)
High – Low	0.1304***	0.1066***	0.1260***	0.1066***	0.1281***	0.1088***
	(4.23)	(3.56)	(4.06)	(3.44)	(4.12)	(3.51)

Table IN3: Simultaneous Leverage-Beta Adjustments in the Same or Opposite Directions: Excluding AUMs of Fixed-income Oriented Funds

This table provides results of panel regressions similar to those in Table 6, with one exception. To obtain asset-implied leverage, we use the asset under management (AUM) of all hedge funds within each fund company, but exclude AUMs of "Convertible Arbitrage", "Fixed Income Arbitrage" and "Managed Futures" funds. We construct dummy variables that correspond to four different scenarios: (1) I{ΔL<0, ΔHB>0}, an indicator variable that takes a value of one if a hedge fund company reduces leverage and increases holding betas simultaneously; (2) I{ΔL>0, ΔHB>0}, which indicates an increase in leverage and holding beta simultaneously; (3) I{ΔL>0, ΔHB<0}, which indicates an increase in leverage and a decrease in holding beta simultaneously; and (4) I{ΔL<0, ΔHB<0}, which indicates a decrease in leverage and holding beta simultaneously. We report the results of the following panel regression:

$$D\{Simultanuous\ Change\}_{i.t} = \alpha + \beta \times HF\ return_{i,t-1,SemiAnnual} + \delta \times M_{i,t-1} + \epsilon_{i,t},$$

where $D\{Simultanuous\ Change\}_{i.t}$ denotes dummy variables in scenarios (1) and (3); $HF\ Return_{i,t-1,SemiAnnual}$ refers to the cumulative returns of hedge fund company i over the previous two quarters. In our regressions, we decompose the lagged semi-annual returns into two signed components. The positive component is calculated as $HF\ return^{+} = HF\ return \times I\{HF\ return > 0\}$, where $I\{.\}$ is an indicator function, and the negative component is calculated as $HF\ return^{-} = HF\ return \times I\{HF\ return \leq 0\}$. In this way, we obtain the positive signed part ($HF\ return^{+}_{i,t-1,SemiAnnual}$) and the negative signed part ($HF\ return^{-}_{i,t-1,SemiAnnual}$) of the lagged semi-annual returns. The vector $M_{i,t-1}$ includes a list of control variables in quarter $t-1$, including hedge funds returns, the value of asset holdings (log dollar), hedge fund flows, the number of funds in the company, as well as the number of stocks invested by the company. We include the hedge fund company (HF family) fixed effects and time (year-quarter) fixed effects in all specifications. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:	I{ΔL<0, ΔHB>0}	I{ΔL>0, ΔHB<0}	I{ΔL<0, ΔHB>0}	I{ΔL>0, ΔHB<0}	I{ΔL<0, ΔHB>0}	I{ΔL>0, ΔHB<0}
	Full Sample		Single-Fund company		Multi-Fund company	
	(1)	(2)	(3)	(4)	(5)	(6)
HF $Return^{+}_{t-1,SemiAnnual}$	0.0064	0.0991**	-0.1730**	0.1983*	0.0772	0.0702
	(0.15)	(2.10)	(-2.05)	(1.91)	(1.34)	(1.20)
HF $Return^{-}_{t-1,SemiAnnual}$	-0.2856***	0.3614***	-0.2351	0.2637*	-0.2943***	0.3827***
	(-3.15)	(4.08)	(-1.43)	(1.74)	(-2.68)	(3.43)
$Assets_{t-1}$	0.0089***	-0.0118***	0.0341**	-0.0371**	0.0074**	-0.0099**
	(3.19)	(-2.72)	(2.39)	(-2.31)	(2.50)	(-2.16)
HF $Flow_{t-1}$	-0.0023	0.0017	-0.0022	0.0020	-0.0016	0.0018
	(-0.83)	(0.58)	(-1.16)	(0.53)	(-0.34)	(0.44)
N_Funds_{t-1}	-0.0003	0.0011				
	(-0.34)	(0.85)				
N_Stocks_{t-1}	0.0127*	-0.0030	-0.0004	0.0257	0.0122	-0.0055
	(1.67)	(-0.31)	(-0.02)	(1.01)	(1.35)	(-0.48)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13906	13906	3633	3633	10273	10273
adj. R-sq	0.111	0.112	0.150	0.147	0.120	0.122

Table IN4: The Hedge Fund *DLCT* Factor, Risk Factors, and Funding Liquidity Factors

This table presents results of regressing the hedge fund *DLCT* factor on well-known risk factors and funding liquidity factors. We estimate the following time-series regression:

$$DLCT\ factor_t = \alpha + \beta \times Risk\ factors_t + \theta \times Funding\ factors_t + \varepsilon_t,$$

The dependent variable $DLCT\ factor_t$ is constructed as the innovation in aggregate hedge fund beta in month t from an AR(1) model. We use holdings of single-fund companies and all fund companies to construct *DLCT* and report results in Columns (1)-(3) and Columns (4)-(6). The vector of $Risk\ factors$ includes the Fama and French three factors, the momentum factor, and Pastor-Stambaugh (2003) liquidity factor. The vector of funding liquidity risk factor includes the intermediary capital risk factor (He, Kelly, and Manela 2017), the 3-month LIBOR rate (Ang et al. 2011), the percentage of loan officers tightening credit standards for commercial and industrial loans (Lee 2013), the term spread (Ang et al. 2011), the TED spread (Gupta and Subrahmanyam 2000), the credit spread (Adrian et al. 2014), and the VIX (Ang et al. 2011). In Columns (3) and (6), we include Boguth and Simutin's (2018) mutual fund holdings-beta based leverage constraint tightness (LCT_MF) factor, and FP's betting-against-beta (BAB) factor. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:	***DLCT*** Factor					
	Single-fund Companies			All-fund Companies		
	(1)	(2)	(3)	(4)	(5)	(6)
Mkt – RF	0.0005			0.0001		
	(0.25)			(0.09)		
SMB	0.0002			0.0006		
	(0.07)			(0.44)		
HML	-0.0009			-0.0005		
	(-0.32)			(-0.34)		
MOM	-0.0012			-0.0004		
	(-0.70)			(-0.38)		
Liquidity	0.0608			0.0169		
	(0.44)			(0.23)		
Intermediary Capital Risk		-0.0976	-0.0316		-0.0212	-0.0027
		(-0.75)	(-0.28)		(-0.29)	(-0.05)
LIBOR Rate		0.0008	-0.0036		0.0051	0.0028
		(0.13)	(-0.63)		(1.40)	(1.03)
Loan Tighten		-0.0001	-0.0001		-0.0000	-0.0000
		(-0.13)	(-0.20)		(-0.13)	(-0.00)
Term Spread		0.0071	-0.0018		0.0111*	0.0055
		(0.66)	(-0.20)		(1.87)	(1.25)
TED Spread		0.0020	-0.0138		-0.0059	-0.0236*
		(0.06)	(-0.51)		(-0.34)	(-1.79)
Credit Spread		0.0709**	0.0544**		0.0202	0.0101
		(2.14)	(1.97)		(1.11)	(0.75)
VIX		-0.0052***	-0.0026*		-0.0014	0.0002
		(-3.22)	(-1.89)		(-1.55)	(0.30)
LCT_MF			0.8838***			0.5859***
			(11.41)			(15.46)
BAB			0.1196			-0.0901
			(0.65)			(-1.00)
Constant	-0.0410***	-0.0214	-0.0006	-0.0147***	-0.0368	-0.0186
	(-4.89)	(-0.46)	(-0.01)	(-3.22)	(-1.43)	(-0.97)
N	300	300	300	300	300	300
adj. R-sq	0.003	0.049	0.344	0.002	0.018	0.469

Table IN5: LP Leverage and Dynamic Fees

This table reports the results of regressing quarterly dynamic fees on asset-implied leverage of hedge fund companies and its interaction with leverage of limited partners (LPs). The panel regression model is:

$$\text{Dynamic fee}_{i.t} = \alpha + \beta \times Leverage_{i,t-1} + \gamma \times LP\ leverage_{i,t-1} + \theta \times Interaction\ term + \delta \times M_{i,t-1} + \epsilon_{i,t},$$

where $Dynamic\ fee_{i.t}$ denotes the dynamic fee (in %) of hedge fund company i in quarter t, which is calculated as the differences between the before-fee and after-fee returns; $Leverage_{i,t-1}$ represents the asset-implied leverage of hedge fund company i in quarter $t-1$; $I\{LP\ Info\}_i$ is an indicator that equals one if the LP leverage information is available for hedge fund company i; $LP\ leverage_i$ denotes the average leverage of all LPs that have made investment in company i. The vector $Interaction\ term$ includes the interaction terms between $Leverage_{i,t-1}$, $I\{LP\ Info\}_i$, and $LP\ leverage_i$. The vector $M_{i,t-1}$ includes a list of control variables in quarter $t-1$, including hedge funds returns, the value of asset holdings (log dollar), hedge fund flows, the number of funds in the company, as well as the number of stocks invested by the company. We include the hedge fund company (HF family) fixed effects and time (year-quarter) fixed effects in all specifications. Panels A and B report results by using unadjusted and the 7-factor adjusted dynamic fees as dependent variables. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Quarterly Dynamic Fees

Dependent Variable:	Quarterly Dynamic Fees (in %)					
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage_{t-1}	0.0103***	0.0104***	0.0106***	0.0107***	0.0103***	0.0107***
	(3.41)	(3.42)	(3.50)	(3.52)	(3.40)	(3.53)
LP Leverage_{t-1}	-0.0002	0.0010	-0.0002	0.0011	-0.0003	0.0010
	(-0.09)	(0.37)	(-0.08)	(0.39)	(-0.12)	(0.38)
Leverage_{t-1} × I{LP Info}	-0.0005	0.0062	-0.0006	0.0061	-0.0005	0.0059
	(-0.07)	(0.56)	(-0.09)	(0.56)	(-0.07)	(0.54)
Leverage_{t-1} × LP Leverage_{t-1}		-0.0005		-0.0005		-0.0005
		(-0.87)		(-0.88)		(-0.90)
Leverage_{t-1} × HF Flow_{t-1}			-0.0023	-0.0023		-0.0029
			(-0.82)	(-0.82)		(-0.98)
LP Leverage_{t-1} × HF Flow_{t-1}					0.0018	0.0010
					(0.55)	(0.24)
Leverage_{t-1} × LP Leverage_{t-1} × HF Flow_{t-1}						0.0003
						(0.67)
HF Return_{t-1}	0.9571***	0.9576***	0.9571***	0.9576***	0.9576***	0.9580***
	(5.96)	(5.97)	(5.96)	(5.97)	(5.97)	(5.97)
Assets_{t-1}	-0.0277***	-0.0284***	-0.0278***	-0.0285***	-0.0276***	-0.0284***
	(-2.71)	(-2.75)	(-2.72)	(-2.76)	(-2.70)	(-2.76)
HF Flow_{t-1}	0.0139	0.0139	0.0203	0.0203	0.0130	0.0207
	(0.89)	(0.89)	(0.97)	(0.97)	(0.80)	(0.97)
N_Funds_{t-1}	-0.0005	-0.0006	-0.0006	-0.0007	-0.0006	-0.0007
	(-0.38)	(-0.44)	(-0.41)	(-0.48)	(-0.38)	(-0.48)
N_Stocks_{t-1}	-0.0039	-0.0040	-0.0042	-0.0044	-0.0038	-0.0043
	(-0.22)	(-0.23)	(-0.24)	(-0.25)	(-0.22)	(-0.25)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11590	11590	11590	11590	11590	11590
adj. R-sq	0.231	0.231	0.231	0.231	0.231	0.231

Panel B: 7-Factor Adjusted Quarterly Dynamic Fees

Dependent Variable:	Quarterly Dynamic Fees 7-Factor Adjusted (in %)					
	(1)	(2)	(3)	(4)	(5)	(6)
$Leverage_{t-1}$	0.0089***	0.0090***	0.0092***	0.0093***	0.0089***	0.0093***
	(3.18)	(3.19)	(3.28)	(3.30)	(3.18)	(3.30)
LP $Leverage_{t-1}$	0.0008	0.0017	0.0008	0.0018	0.0008	0.0018
	(0.36)	(0.68)	(0.38)	(0.71)	(0.36)	(0.71)
$Leverage_{t-1}$ × I{LP Info}	-0.0003	0.0045	-0.0004	0.0044	-0.0003	0.0043
	(-0.04)	(0.43)	(-0.07)	(0.42)	(-0.04)	(0.42)
$Leverage_{t-1}$ × LP $Leverage_{t-1}$		-0.0004		-0.0004		-0.0004
		(-0.66)		(-0.68)		(-0.70)
$Leverage_{t-1}$ × HF $Flow_{t-1}$			-0.0027	-0.0027		-0.0031
			(-1.14)	(-1.14)		(-1.23)
LP $Leverage_{t-1}$ × HF $Flow_{t-1}$					-0.0002	-0.0006
					(-0.05)	(-0.15)
$Leverage_{t-1}$ × LP						0.0002
$Leverage_{t-1}$ × HF $Flow_{t-1}$						(0.68)
HF $Return_{t-1}$	0.6459***	0.6462***	0.6459***	0.6462***	0.6458***	0.6462***
	(4.80)	(4.81)	(4.80)	(4.80)	(4.80)	(4.80)
$Assets_{t-1}$	-0.0223**	-0.0228**	-0.0224**	-0.0229**	-0.0223**	-0.0229**
	(-2.42)	(-2.45)	(-2.43)	(-2.46)	(-2.41)	(-2.46)
HF $Flow_{t-1}$	0.0135	0.0135	0.0211	0.0211	0.0135	0.0215
	(0.88)	(0.88)	(1.03)	(1.03)	(0.84)	(1.03)
N_Funds_{t-1}	-0.0003	-0.0003	-0.0003	-0.0004	-0.0003	-0.0004
	(-0.20)	(-0.25)	(-0.25)	(-0.30)	(-0.20)	(-0.30)
N_Stocks_{t-1}	-0.0049	-0.0050	-0.0053	-0.0055	-0.0049	-0.0054
	(-0.32)	(-0.33)	(-0.34)	(-0.35)	(-0.32)	(-0.35)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11590	11590	11590	11590	11590	11590
adj. R-sq	0.187	0.187	0.187	0.187	0.187	0.187

Table IN6: LP Leverage and Simultaneous Adjustments in Leverage and Investment Policies

This table reports the results of regressing hedge funds' simultaneous adjustments in leverage and investment policies on hedge funds' past returns, the leverage of limited partners (LPs), and their interactions. We construct dummy variables that correspond to four different scenarios: (1) I{ΔL<0, ΔHB>0}, an indicator variable that takes a value of one if a hedge fund company reduces leverage and increases holding betas simultaneously; (2) I{ΔL>0, ΔHB>0}, which indicates an increase in leverage and holding beta simultaneously; (3) I{ΔL>0, ΔHB<0}, which indicates an increase in leverage and a decrease in holding beta simultaneously; and (4) I{ΔL<0, ΔHB<0}, which indicates a decrease in leverage and holding beta simultaneously. This table reports the results of the following panel regression:

$$D\{Simultanuous\ Change\}_{i.t} = \alpha + \beta \times HF\ return_{i,t-1,SemiAnnual} + \gamma \times LP\ leverage_{i,t-1}$$
$$+\theta \times Interaction\ term + \delta \times M_{i,t-1} + \epsilon_{i,t},$$

where $D\{Simultanuous\ Change\}_{i.t}$ denotes the two dummy variables in scenarios (1) and (3); $HF\ Return_{i,t-1,SemiAnnual}$ refers to the cumulative returns of hedge fund company *i* over the previous 6 months. We decompose the lagged semi-annual returns into two signed components. The positive component is calculated as $HF\ return^{+} = HF\ return \times I\{HF\ return > 0\}$, where $I\{.\}$ is an indicator function, and the negative component is calculated as $HF\ return^{-} = HF\ return \times I\{HF\ return \leq 0\}$. In this way, we obtain the positive signed part ($HF\ return^{+}_{i,t-1,SemiAnnual}$) and the negative signed part ($HF\ return^{-}_{i,t-1,SemiAnnual}$) of the lagged semi-annual returns. $I\{LP\ Info\}_i$ is an indicator that equals one if the LP leverage information is available for hedge fund company i. $LP\ leverage_i$ denotes the average leverage of all LPs that have made investment in company i. The vector $Interaction\ term$ includes the interaction terms between $HF\ Return_{i,t-1,SemiAnnual}$, $I\{LP\ Info\}_i$, and $LP\ leverage_i$. The vector $M_{i,t-1}$ includes a list of control variables in quarter $t-1$, including hedge funds returns, the value of asset holdings (log dollar), hedge fund flows, the number of funds in the company, as well as the number of stocks invested by the company. We include the hedge fund company (HF family) fixed effects and time (year-quarter) fixed effects in all specifications. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:	I{ΔL<0, ΔHB>0}			I{ΔL>0, ΔHB<0}		
	(1)	(2)	(3)	(4)	(5)	(6)
HF Return$^{+}_{t-1,\text{SemiAnnual}}$	0.0353	0.0348	0.0316	0.0822	0.0819	0.0859
	(0.64)	(0.64)	(0.58)	(1.57)	(1.56)	(1.64)
HF Return$^{-}_{t-1,\text{SemiAnnual}}$	-0.3475***	-0.3462***	-0.3600***	0.2472**	0.2531***	0.2514**
	(-3.13)	(-3.12)	(-3.22)	(2.56)	(2.61)	(2.56)
HF Return$^{+}_{t-1,\text{SemiAnnual}}$	-0.1043	-0.0846	-0.0815	0.0928	0.0893	0.0866
× I{LP Info}	(-1.18)	(-0.95)	(-0.92)	(0.95)	(0.90)	(0.87)
HF Return$^{-}_{t-1,\text{SemiAnnual}}$	0.0498	0.0504	0.0486	0.1484	0.2281	0.2291
× I{LP Info}	(0.30)	(0.29)	(0.28)	(0.98)	(1.50)	(1.51)
HF Return$^{+}_{t-1,\text{SemiAnnual}}$		-0.0012**	-0.0013**		0.0005	0.0005
× LP Leverage$_{t-1}$		(-2.34)	(-2.37)		(1.41)	(1.45)
HF Return$^{-}_{t-1,\text{SemiAnnual}}$		-0.0003	-0.0001		-0.0094**	-0.0094**
× LP Leverage$_{t-1}$		(-0.08)	(-0.03)		(-2.31)	(-2.31)
HF Return$^{+}_{t-1,\text{SemiAnnual}}$			0.0438			-0.0452
× HF Flow$_{t-1}$			(0.97)			(-1.54)
HF Return$^{-}_{t-1,\text{SemiAnnual}}$			-0.2947			0.0118
× HF Flow$_{t-1}$			(-1.44)			(0.06)
LP Leverage$_{t-1}$	-0.0000	0.0001	0.0001	-0.0001	-0.0003***	-0.0003***
	(-0.19)	(0.52)	(0.53)	(-1.10)	(-2.94)	(-2.95)
Assets$_{t-1}$	0.0107**	0.0108**	0.0108**	-0.0108***	-0.0108***	-0.0108***
	(2.49)	(2.50)	(2.50)	(-2.80)	(-2.79)	(-2.79)
HF Flow$_{t-1}$	-0.0019	-0.0019	-0.0051	0.0022	0.0021	0.0043
	(-0.69)	(-0.69)	(-1.47)	(0.71)	(0.69)	(1.23)
N_Funds$_{t-1}$	0.0010	0.0009	0.0009	0.0004	0.0004	0.0004
	(0.84)	(0.82)	(0.82)	(0.36)	(0.35)	(0.35)
N_Stocks$_{t-1}$	0.0043	0.0048	0.0048	-0.0035	-0.0035	-0.0034
	(0.47)	(0.53)	(0.53)	(-0.39)	(-0.38)	(-0.38)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HF Family FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13906	13906	13906	13906	13906	13906
adj. R-sq	0.046	0.046	0.046	0.065	0.065	0.065

Table IN7: Fama-MacBeth Regressions of Monthly Stock Returns on Exposure to the *DLCT* Factor (Constructing the *DLCT* Factor Using All Hedge Fund Companies)

This table reports the results of Fama-MacBeth regressions of monthly stock returns on their exposures to the hedge fund *DLCT* (the delegated leverage constraint tightness) factor. Stock returns (in percent) in month t + 1 are regressed on $Exposure^{DLCT}$ computed as of month t, which is the stock's exposure to the *DLCT* factor. The variable *DLCT* is the aggregate hedge fund beta, estimated by using the value-weighted hedge fund holding betas. The *DLCT* factor is the innovations in the variable *DLCT* from an AR (1) model. We use the aggregate holdings of all hedge fund companies to construct *DLCT*. Other independent variables include the stock's market equity, book-to-market ratio, profits-to-assets ratio, asset growth rate, stock return run up, reversals, and idiosyncratic volatility in month *t*. All independent variables are normalized to have a cross-sectional standard deviation of one. Reported are the average coefficients and the Newey and West (1987) T-statistics. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Dependent Variable:	Stock Return$_{t+1}$ (Monthly, in %)					
	Full Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
$Exposure^{DLCT}_t$	-0.1370***	-0.0991**	-0.0922*	-0.1066*	-0.1154**	-0.0962**
	(-2.84)	(-1.97)	(-1.86)	(-1.90)	(-2.16)	(-2.04)
Market Equity$_t$		-0.2220*	-0.2265*	-0.2386**	-0.1810	-0.1857**
		(-1.83)	(-1.87)	(-2.00)	(-1.62)	(-2.26)
Book to Market Ratio$_t$		0.2043**	0.2159**	0.1619*	0.1957**	0.1896**
		(2.21)	(2.32)	(1.82)	(2.32)	(2.45)
Profits_to_Assets$_t$			0.4999**	0.4696**	0.5068**	0.4988**
			(2.30)	(2.14)	(2.30)	(2.35)
Asset_Growth$_t$				-0.3743***	-0.4518***	-0.4424***
				(-3.48)	(-4.11)	(-4.08)
Stock Return Run Up$_t$					0.0571	0.0750
					(0.50)	(0.70)
Reversals$_t$					-0.5365***	-0.5562***
					(-5.85)	(-5.97)
Idiosyncratic Volatility$_t$						-0.0215
						(-0.15)