Leveraged Funds and the Shadow Cost of Leverage Constraints*

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Abstract

Using the most comprehensive dataset of leveraged funds, we estimate the market-wide shadow cost of leverage constraints and examine its pricing implications. The annualized shadow cost averages around 0.51% from 2006 to 2016. It spikes upon quarter-ends when financial intermediaries make mandatory reporting, positively predicts future betting-against-beta (BAB) returns, and negatively correlates with contemporaneous BAB returns. Stocks that underperform when the shadow cost increases earn 0.75% more per month. Our shadow cost measure helps identify the supply and demand shifts in the leverage market. Overall, our measure fits the predictions of leverage-constraint based theories better than the widely used TED spread.

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"Embedded leverage...is the only reason for the existence of leveraged ETFs." – Frazzini and Pedersen (2012)

1. Introduction

A number of recent theories have explored the proposition that marginal investors' ability to take leverage is a key determinant of asset prices. The tightness of leverage constraints is measured by the shadow cost, i.e., the difference between marginal investors' funding cost and the risk-free rate when the credit risk is fully hedged (Garleanu and Pedersen (2011)).[1] Despite its central role, data on the shadow cost of leverage constraints are lacking because financing terms are typically negotiated bilaterally (and confidentially) between lenders and leveraged investors. As a result, existing empirical studies mostly use the Treasury-Eurodollar (TED) spread as the shadow cost measure.[2]

Our key innovation is to construct a market-wide cost of leverage measure by using market data on leveraged funds. Leveraged funds provide an attractive alternative to the TED spread for measuring the shadow cost of leverage constraints. First, leveraged funds obtain leverage directly from major broker-dealers, and given their passive portfolio choice, they focus on obtaining the leverage at a competitive market price. Thus, compared to the indicative LIBOR rate, the cost of leverage for an average leveraged fund is potentially a more accurate measure of the market price at which financial intermediaries provide funding to arbitragers such as hedge funds.[3] Second, leveraged funds' borrowing are conducted through derivatives that are marked to market every day with collateral posted. Consequently, their borrowings have very low credit risk and thus offer the potential to construct a shadow cost of leverage constraints measure that is much less contaminated by the credit risk than the TED spread.

[1]The shadow cost of leverage constraints is formally the Lagrange multiplier of the constraint on the marginal investor's maximum risk exposure in the utility maximization problem. In traditional theories where the capital is unconstrained, the shadow cost of leverage constraints is zero. In reality, the capital is constrained due to banks' capital requirements, investors' margin requirements, or simply investors' unwillingness to use explicit leverage.

[2]See, e.g., Brunnermeier, Nagel, and Pedersen (2008); Cornett, McNutt, Strahan, and Tehranian (2011); Moskowitz, Ooi, and Pedersen (2012); Asness, Moskowitz, and Pedersen (2013); Frazzini and Pedersen (2014).

[3]The funding cost paid by leveraged funds is the marginal benefit received by broker-dealers for providing the funding, which in turn reflects broker-dealers' shadow cost of capital in equilibrium. In addition, leveraged funds' cost of leverage plus their expense ratios is the cost of leverage borne by investors of leveraged funds. Therefore, leveraged funds' cost of leverage can be informative about the marginal investor's shadow cost of leverage constraints, when either broker-dealers or investors in leveraged funds consider cost of leverage when making portfolio choices.

As Frazzini and Pedersen (2012) highlight, estimating the cost of leverage for leveraged funds is particularly straightforward given their unique feature of targeting a *constant daily* leverage.[4] We take the difference between daily gross returns on leveraged funds and the target multiple of the underlying index returns, and use it as leverage funds' all-in cost of leverage. We then use the full cross section of leveraged funds to infer the market-wide cost of leverage at a point of time. To this end, we assemble the most comprehensive dataset on leveraged funds known to the literature that includes all leveraged funds, dead or active, that rebalance daily to track a constant multiple of the daily performance of an underlying index between 2006 and 2016.

We start the empirical analysis by correlating our cost of leverage measure, the (cross-sectional) median cost of leverage for all bullish leveraged funds, with benchmark interest rates.[5] Consistent with the characterization of a funding cost measure, we find our cost of leverage measure tracks benchmark interest rates.[6] The Garleanu and Pedersen (2011) model demonstrates that the shadow cost of leverage constraints is the interest-rate spread between the borrowing rate of leverage constrained investors and the collateralized interest rate. We thus compute our baseline shadow cost measure as the interest-rate spread between our cost of leverage measure and the general collateral (GC) repo rate.[7]

We find that our shadow cost estimate averages 0.30% per annum and is almost always positive after the 2007–2009 financial crisis. During the crisis, our baseline shadow cost estimate frequently drops below zero largely because security lending income is substantially higher, lowering the effective funding cost. Adjusting for the security lending income, our shadow cost estimate averages 0.51% per annum.

We use our shadow cost measure and the TED spread as proxies for the shadow cost of leverage constraints in tests of four hypotheses from the Garleanu and Pedersen (2011) model. The model predicts that (i) the shadow cost of leverage constraints is higher when the constraints are more binding; (ii) when the shadow cost increases, the required return for high-beta stocks that provide embedded leverage decreases relative to low-beta stocks,

[4]Frazzini and Pedersen (2012) study the pricing of embedded leverage in different financial instruments including 7 leveraged funds.

[5]We focus on bullish funds in this paper because bearish funds earn rebate rates instead of paying cost of leverage. More discussions are in Subsection 3.1.

[6]Our benchmark interest rates include the one-month Treasury bill rate, the general collateral (GC) repo rate, which is the inter-broker collateralized overnight borrowing rate, and the effective fed funds rate (EFFR), which is the unsecured overnight borrowing rate between depository institutions in the fed funds market.

[7]We use the GC repo rate in our baseline estimation to closely follow the collateralized interest rate in the Garleanu and Pedersen model. We also compute the spread over EFFR as a robustness check.

and hence (iii) high-beta stocks would have contemporaneously higher returns; (iv) exposure to time variation in the shadow cost is priced in the cross section of expected stock returns.[8] These predictions are shared by other leverage constraint based theories.

Our first set of tests examines the prediction in hypothesis (i) that the shadow cost is higher in periods when the leverage constraints are likely more binding. We find that both our shadow cost measure, after adjusting for security lending income, and the TED spread are substantially higher in bear market states defined using either 3-year cumulative market returns (Cooper, Gutierrez, and Hameed (2004)) or VIX. These results are consistent with the intuition that the leverage constraints are more binding when market participants suffer large losses and when the volatility is high (Ang, Gorovyy, and van Inwegen (2011)). However, the increase in funding costs could simply due to an increase in credit risk rather than a tighter leverage constraint. We conduct a sharper test of hypothesis (i) by examining the changes in our shadow cost measures and the TED spread upon quarter-ends.[9] We find that our shadow cost measures increase by 1.2 percentage points on an annualized basis upon quarter-ends, which is statistically highly significant, while the corresponding changes in the TED spread are minimal and insignificant.

Our second set of results test for a positive relation between the shadow cost and future BAB returns as predicted in hypothesis (ii).[10] We follow the empirical specification in Boguth and Simutin (2018) by regressing BAB returns over the next 1, 6, 12 months on lagged moving averages of shadow cost measures. We find that our shadow cost measure strongly and positively predicts future BAB returns. In contrast, we find the TED spread predicts future BAB returns with a theoretically incorrect negative sign, confirming Frazzini and Pedersen (2014)'s findings. The positive relation between our shadow cost measure is robust to controlling for the TED spread, the LCT measure in Boguth and Simutin (2018), and the MD measure in Asness, Frazzini, Gormsen, and Pedersen (2016).

Somewhat surprisingly, we find that the LCT measure, which is the market beta of stock holdings by active mutual funds, predicts future BAB returns with a negative sign in our sample period. This contrasts with the findings in Boguth and Simutin (2018) that the LCT

[8]Though the last prediction is not explicitly stated in Garleanu and Pedersen (2011), it is a natural implication from the model.

[9]The bank window dressing literature suggests that banks have incentive to shrink the size of balance sheet upon financial reporting days because of capital ratio requirements. Thus, the capital constraint is likely to be more binding while the credit risk stays the same upon quarter-ends.

[10]The BAB portfolio put forth by Frazzini and Pedersen (2014) is a zero investment portfolio that takes a levered long position in low beta stocks and a unlevered short position in high beta stocks that has a zero ex-ante CAPM beta.

measure positively predicts future BAB returns in their longer sample period. We connect these seemly contradictory results to the broader discussion on the relation between the level of leverage and the tightness of leverage constraints in the literature.[11] We highlight that quantity and price can move in the same or opposite direction depending on whether supply or demand shifts are driving the equilibrium. Specifically, if mutual funds' demand curve for the leverage implicit in high-beta stocks shifts outward, the aggregate mutual fund beta increases and the leverage constraints is more binding (i.e., a higher shadow cost). On the other hand, if the supply curve for leverage shifts outward, the aggregate mutual fund beta can still increase while the constraint is less binding.[12] Consistent with this supply-demand prediction, we find a more positive relation between the aggregate mutual fund beta and future BAB returns when the LCT measure and our shadow cost measure move in the same direction.

Our third set of tests analyze the relation between the shadow cost estimates and contemporaneous BAB returns. We find a negative and significant correlation between our shadow cost measure and contemporaneous BAB returns, consistent with hypothesis (iii). This negative relation is robust to controlling for the negative correlation between the TED spread and contemporaneous BAB returns documented in Frazzini and Pedersen (2014) and robust to controlling for VIX and the market returns.

Our final set of tests examine the implications of leverage constraints on the cross-section of stock returns. We run rolling regressions of excess stock returns on market excess returns and the AR(1) innovations in our shadow cost measure or the TED spread. We find strong evidence that exposure to our shadow cost measure negatively predicts stock returns in the cross section, supporting hypothesis (iv). In contrast, we find no evidence that exposure to the TED spread is priced. When we sort stocks into quintile portfolios based on their sensitivities to our shadow cost measure, we find that stocks in the bottom quintile (i.e., stock underperform when the shadow cost is high) on average outperform stocks in the top quintile by 0.75% per month. Further analysis shows that this risk premium cannot be explained by exposures to standard risk factors, such as Fama-French five factors, or by exposures to other proxies for funding conditions.

Our main contribution to the empirical asset pricing literature is to demonstrate an vi-

[11]The LCT measure, i.e., the aggregate mutual fund beta, is interpreted as the implicit aggregate leverage taken by mutual funds in Boguth and Simutin (2018).

[12]A simple story is that the funding constraint is less binding for arbitragers, who go long low-beta stocks and short high-beta stocks more aggressively, making high-beta stocks cheaper to purchase for active mutual funds.

able alternative to the TED spread for measuring the shadow cost of leverage constraints. Our measure and the TED spread are different in several important aspects. First, the TED spread mostly measures the credit risk of unsecured lending to large commercial banks. However, the shadow cost of leverage constraints can arise independent of the credit risk (Garleanu and Pedersen (2011)). In this aspect, leveraged funds provide an excellent empirical setting to study the shadow cost of leverage constraints when the complication from credit risk is minimal. Second, when banks' capital constraint is tight, the banks' marginal cost of capital is likely higher than the LIBOR rate (Kisin and Manela (2016)). Furthermore, the marginal leveraged investors in the stock market may not borrow at the LIBOR rate.[13] In contrast, leveraged fund data provide a rare opportunity to infer the market price at which major broker-dealers provide fundings to the leveraged investors. Overall, our findings suggest our measure fits their model's predictions better than the TED spread.

Our paper is related to several strands of literature. First, Koijen and Yogo (2016) and Kisin and Manela (2016) are two recent studies that explicitly quantify the shadow cost of capital for market participants (life insurers and banks, respectively). The average shadow cost of banks' tier 1 risk-based capital ratio requirement estimated in Kisin and Manela (2016) is 30 bps annum, which is is identical to our baseline estimate of the average annualized shadow cost of leverage constraints.[14]

Second, our results are also related to the literature on the interaction between limits to arbitrage and constraints on financial intermediaries exemplified by Du et al. (2018), who find the violation of covered interest rate parity is more pronounced when the financial contracts straddle quarter-ends. Consistent with their interpretation that the financial intermediaries are less willing to lend their balance sheet upon financial reporting days, our estimate of the shadow cost of leverage constraints rises substantially during quarter-ends. Our findings thus lend support to the key assumption in intermediary asset pricing models that the shadow cost of capital constraints faced by banks is closely related to the shadow cost of leverage constraints faced by the marginal investor.

Third, our paper adds to recent empirical research that investigates the time-series and cross-sectional pricing implications of leverage constraints. Frazzini and Pedersen (2014); Asness et al. (2016); Boguth and Simutin (2018) examine the relation between leverage

[13] Garleanu and Pedersen (2011) raise these two caveats when they use the TED spread as a proxy for the shadow cost of capital to test their theoretical predictions.

[14] Estimates based on other capital ratio requirements are slightly lower. The loophole used for estimating the shadow cost in Kisin and Manela (2016) was closed in January 2010. Koijen and Yogo (2016) find that the shadow cost of capital for life insurers can be as high as \$0.96 per dollar of statutory capital.

constraints and future BAB returns. They use the TED spread, the ratio of the margin debt over the total market capitalization for NYSE stocks, and the aggregate active mutual funds market beta, respectively, as the proxy for the tightness of leverage constraints. Adrian, Etula, and Muir (2014); He, Kelly, and Manela (2017); Boguth and Simutin (2018) examine the cross-sectional implication of leverage constraints. They use the leverage of security broker-dealers, the equity capital ratio of primary dealers, and the aggregate active mutual funds market beta, respectively, as a proxy for the tightness of the leverage constraints that drives the stochastic discount factor (SDF) in intermediary asset pricing models. All of these measures except for the TED spread are "quantity" measures pertaining to the level of leverage, which is in itself an interesting phenomena but distinct from "price" measures pertaining to borrowing rates. We add to this body of work by using the difference between leveraged funds' funding rate and a benchmark interest rate as a direct estimate of the shadow cost of leverage constraints. Empirically, our time-series and cross-sectional test results are robust to control for these existing measures. Conceptually, quantity and price can comove in the same or opposite direction depending on whether demand or supply shifts are driving the equilibrium.[15] We demonstrate results consistent with this demand-supply perspective when using the aggregate mutual fund beta in Boguth and Simutin (2018) and our shadow cost measure as the price-quantity pair to identify demand and supply shifts in the leverage market.

Finally, our paper contributes to the literature on leveraged funds by assembling a comprehensive dataset that we believe include all leveraged funds, dead and active, that track a constant multiple of daily index returns.[16] Frazzini and Pedersen (2012) are the first to

[15] Ang, Gorovyy, and van Inwegen (2011); He, Kelly, and Manela (2017), among others, document that the equilibrium leverage can be either high or low when the capital constraint is tight (i.e., the shadow cost is high), depending on whether the binding constraint is a "equity constraint" (He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014)) or a "debt constraint" (Brunnermeier (2009); Adrian and Shin (2013)). The debt constraint can be interpreted as supply shocks, e.g., lenders reduce leverage when the risk is high. The equity constraint can be interpreted as demand shocks, e.g., loss of arbitragers' capital raises risky assets' expected returns and thus arbitragers' optimal leverage is higher. See He and Krishnamurthy (2018) for a review of the intermediary asset pricing literature.

[16] There is a growing literature using leveraged fund data. See, e.g., Avellaneda and Zhang (2010) and Lu, Wang, and Zhang (2009) for studies on the deviation between the long-term performance (instead of the one-day performance as promised in the prospectus) of leveraged funds and that of a levered buy-and-hold position in the underlying index. See, e.g., Charupat and Miu (2011), Tang and Xu (2013), and Jiang and Yan (2016) for studies on the market price discounts and premiums of leveraged funds. With the growth of the leveraged fund industry, there also has been increasing concerns regarding the implications of the daily rebalancing of leveraged funds, which is always in the same direction as the benchmark returns for both bullish and bearish funds, on market liquidity and volatility. See, e.g., Cheng and Madhavan (2009); Tuzun (2014); Ivanov and Lenkey (2014).

examine the cost of embedded leverage in leveraged funds. They use the daily returns of 7 leveraged funds between 2006 and 2010. Tang and Xu (2013) investigate the determinants of the deviation between daily fund returns and the target returns using 12 leveraged funds between 2006 and 2011. They find that the most important determinant of the deviation is the prevailing interest rate. Tuzun (2014) and Jiang and Yan (2016) provide the two most comprehensive leveraged funds in the literature, collected from Morningstar Direct and Bloomberg, respectively. Tuzun (2014) and Jiang and Yan (2016) focus exclusively on leveraged ETFs, whereas our dataset includes not only leveraged ETFs but other types of leveraged funds such as open-end mutual funds. As a result, our dataset includes twice to four times as many funds, collected mainly from the Center for Research in Security Prices Survivor-Bias-Free US Mutual Fund Database and supplemented by data from Bloomberg.[17]

The remainder of this paper is organized as follows. In Section 2, we provide the institutional background for leveraged funds. In Section 3, we describe the theory behind and the empirical setup for our key empirical measure. Section 4 describes our comprehensive daily leveraged fund dataset. Section 5 examines our cost of leverage measure and our spread measure for the shadow cost of leverage constraints. Sections 6 to 9 use our spread measure to study the asset pricing implications of leverage constraints. We conclude in Section 10.

2. Institutional background

Leveraged funds are open-end mutual funds, exchange-traded funds (ETFs), and exchange-traded notes (ETNs) that seek to track a multiple of the returns of a benchmark index, before fees and expenses. While a handful of leveraged and inverse mutual funds first emerged in 1993 in the United States, the number of leveraged funds increased substantially after ProShares offered the first leveraged (and inverse) ETFs in 2006.[18] The demand for leveraged funds has been growing because leveraged funds offer a convenient, transparent, and potentially less expensive way to obtain leverage. Using the data we assemble, we find that the number of leveraged funds has grown from 127 to around 400 and the exposure value has grown from \$10 billion to over \$75 billion between 2006 and 2016.[19] Most leveraged funds are managed by four investment companies, Rydex, Profunds, Direxion, and ProShares, with

[17]More details are in the Data Section.

[18]http://www.proshares.com/media/documents/geared_investing.pdf

[19]The size of the leveraged fund industry is smaller than that of the equity long-short hedge fund sector (\$193.6 billion as of September 2016 according to https://www.barclayhedge.com). As we explain later, there are reasons to believe the cost of leverage for leveraged funds is informative about the cost of leverage for other leveraged investors such as hedge funds.

the former two focusing on leveraged mutual funds and the latter two focusing on leveraged ETFs.

Figure 3 illustrates a typical leveraged fund using the official webpage for ProShares Ultra Financials. The investment objective is highlighted in bold at the top, as "[The fund] seeks daily investment results, before fees and expenses, that correspond to two times (2x) the daily performance the Dow Jones U.S. Financials Index." The fund emphasizes that the promised leverage multiple pertains only to daily returns based on NAV and explicitly warns that returns over periods other than one day can differ from two times the benchmark returns.[20] Furthermore, the leveraged fund discloses its annualized expense ratio, the daily net asset value (NAV), and the daily holdings.

A snapshot of ProShares Ultra Financials' daily holdings in sub-figure (b) of Figure 3 demonstrates how the 2x leverage is achieved. The total market value of this fund is \$906,931,618. The fund obtains two times worth of exposure over its market value by investing \$762,011,691 in the constituents of the Dow Jones U.S. Financials Index and acquires the remaining exposure of \$1,050,292,778 via equity swaps.[21]

More generally, equity swaps are the most common derivative used by leveraged funds to maintain their target leverage. In such swap transactions, leveraged funds are the equity return leg receiver and the floating interest rate leg payer, effectively borrowing from their swap counterparties. The interest rate leg is typically the LIBOR rate plus a markup. The equity return leg is typically the total return of the index from the initial price specified in the swap contract. Leverage funds pay transaction costs implicitly as the initial price is based on the cost at which swap counterparties can acquire the equity exposure from the cash or futures markets.

The counterparty risk for these swap transactions is relatively low because the swaps are marked to market daily and collateral equal to the value owed to the counterparty are required. To further reduce the counterparty risk, leveraged funds enter swap contracts only with major global financial institutions and they use multiple counterparties simultaneously.[22] For example, sub-figure (b) of Figure 3 shows that ProShares Ultra Financials'

[20]Therefore, our daily returns are based on NAV, which in this case is calculated by JPMorgan Chase Bank, National Association at 4:00 pm ET and reflects the fundamental value of securities owned by the fund.

[21]The fund also holds \$144,919,927 in cash. As a result, the exposure calculation is $\frac{Exposure}{NAV} = \frac{Swap\ Notional + Index\ Investment}{Swap\ Net\ Value + Index\ Investment + Cash} = \frac{1{,}050{,}292{,}778 + 762{,}011{,}691}{0 + 762{,}011{,}691 + 144{,}919{,}927} = 1.998$. For ProShares Ultra Financials observed on 7/24/2018, the percentage of the total exposure due to swaps versus investing in the underlying is 58% vs. 42%.

[22]The funds disclose that they may not always be successful at obtaining collateral from the counterparty collateral. Another potential reason for having multiple counterparties is to prevent counterparties from

swap counterparties include UBS, Deutsche Bank, Morgan Stanley, Bank of America, Societe Generale, Citibank, Goldman Sachs, and Credit Suisse, which collectively represents a list of the largest broker-dealers in the market. The fact that leveraged funds borrow directly and simultaneously from multiple major broker-dealers motivates our hypothesis that the funding costs of leverage funds can be informative about the market price at which major broker-dealers provide funding to other leveraged investors.

3. Model

3.1. Empirical model for inferring the cost of leverage

This subsection develops the empirical model we use to infer the financing cost of leverage funds from their daily returns. We compute the (before fees) performance shortfall α_{it} for a leveraged fund i seeking δ times the daily performance of an index j as follows:

$$\alpha_{it} \equiv r_{it} - \delta b_{jt}, \tag{1}$$

where r_{it} is the daily gross return of the leverage fund computed as the sum of the daily expense ratio and the after-fee NAV return, and b_{jt} is the benchmark return.

The performance shortfalls of bullish and bearish funds are driven by different factors. As illustrated by the example of ProShares Ultra Financials in Section 2, the portfolio holdings per dollar of assets under management (AUM) for a typical δx bullish leveraged fund can be modeled as an investment of \$1 in the underlying benchmark and an additional $\$\,(\delta-1)$ exposure acquired from the financial intermediaries at a cost r^c_{it}. Hence the performance shortfall α_{it} for a bullish fund is

$$\alpha_{it} = -\left(\delta - 1\right) r^c_{it} \;\; \left(\delta > 1\right), \tag{2}$$

where $\delta - 1$ is the amount of financing needed and r^c_{it} is the cost of leverage. We use r^c_{it} to capture the all-in cost of maintaining the constant level of leverage, including costs such as interest payments and transaction costs.[23]

In contrast, a δx bearish fund goes short $\$\delta$ of the underlying benchmark and essentially lends securities to, rather than borrows funding from, the counterparty and earns the rebate

front running the orders (we thank Tugkan Tuzun for suggesting this possibility).

[23]In a typical total return equity swap transaction, the transaction costs are embedded in the swap spread.

rate (the difference between the prevailing risk-free rate and the security lending fee). Hence the performance shortfall α_{it} for a bullish fund is

$$\alpha_{it} = r_{ft} + |\delta|\, r_{it}^{rebate} \;\; (\delta \leq -1)\,. \tag{3}$$

Since this paper analyzes the cost of leverage, we focus on bullish funds whose performance shortfalls are more closely related to the cost of leverage r_{it}^{c}. We then take into account two complications in the data. First, we recognize that the true leverage multiple can differ from the target leverage multiple (δ). The resulting tracking error means α_{it} in Eq. (2) is a noisy proxy for r_{it}^{c}. We mitigate the influence of measurement errors by taking cross-sectional and time-series averages to increase the power of our empirical tests.

Second, a bullish fund can potentially earn security lending fees by lending out the basket of stocks it owns. In practice, because leveraged funds rebalance much more frequently than unlevered index funds, it is more costly for leveraged funds to set aside substantial amounts of assets for security lending purposes. Nevertheless, security lending fees can become an important source of income when the fees are high in bear markets. To address this problem, for each index j, we use the value-weighted performance shortfall for unlevered index funds as a control for security lending fees. The idea is that unlevered index funds also earn security lending fees on their AUM, but since they are unlevered they do not pay cost of leverage. This control is defined as

$$\alpha_j^{1X} \equiv \sum_i \omega_{it} r_{it} - b_{jt}. \tag{4}$$

, where i denotes unlevered index funds benchmarked to index j and the weight ω_{it} is proportional to the total net asset value.[24] Because unlevered funds also have tracking errors, we recognize that α_j^{1X} is a noisy proxy for the security lending fees.

Based on Eqs. (2) and (4), we compute our baseline market-wide cost of leverage measure

[24]Again r_{it} is the gross return after adding back the expense ratio. α_j^{1X} also serves as a control for rebalancing costs associated with unlevered funds for index j.

as the cross-sectional median of $\frac{\alpha_{it}}{1-\delta}$ across all bullish funds[25]

$$r_t^c \equiv \text{Cross Sectional Median of } \frac{\alpha_{it}}{1-\delta},\ \delta > 0. \tag{5}$$

We also compute the cost of leverage measure adjusted for security lending income as

$$r_t^{c,\text{adj}} \equiv \text{Cross Sectional Median of } \frac{\alpha_{it} - \alpha_{jt}^{1X}}{1-\delta},\ \delta > 0. \tag{6}$$

3.2. Theoretical motivation for the shadow cost of leverage constraints

We discuss the relation between our cost of leverage measure (r_t^c) and the shadow cost of leverage constraints in the theoretical framework of Garleanu and Pedersen (2011). Consider the following dynamic programming problem of a representative investor,

$$\max_{\{\theta_{it}, C_t, \eta_{ut}\}} E_t \int_0^\infty e^{-\rho s} u\left(C_s\right) ds \tag{7}$$

$$\frac{dW_t}{W_t} = \left(r_{ft} + \eta_{ut}\left(r_{ut} - r_{ft}\right) + \sum_i \theta_{it}\left(\mu_{it} - r_{ft}\right) - \frac{C_t}{W_t}\right) dt + \sum_i \theta_{it}\sigma_{it} d\omega_t \tag{8}$$

where $u\left(C_s\right)$ is the utility function for consumption C_s, W_t is the investors' wealth at time t with θ_{it} being the proportion of wealth invested in asset i. Asset i's prices follow an Itô process with innovation $d\omega_t$, expected return μ_{it}, and volatility σ_{it}. Investors choose their collateralized and uncollateralized borrowings given the risk-free rate r_{ft} and the uncollateralized rate r_{ut}.[26] Investors' portfolio choice is subject to the margin constraint

$$\sum m_{it}\left|\theta_{it}\right| + \eta_{ut} \leq 1, \tag{9}$$

where η_{ut} is the uncollateralized borrowing as a proportion of wealth. The Garleanu and Pedersen (2011) specification of the margin constraint in Eq. (9) models the real-world investors' problem that both long and short positions in risky assets require collateral m_{it} in their margin accounts. Since uncollateralized borrowing relaxes the leverage constraint

[25] While more advanced filtering techniques can potentially improve the signal to noise ratio, we decided to keep the measure simple and easy to replicate. We use the median instead of the mean because the former is more robust to extreme values. See a related discussion here, https://www.newyorkfed.org/medialibrary/media/markets/EFFR-technical-note-070815.pdf, in which the Federal Reserve Bank of New York explains its 2015 methodology change from using the mean transaction rate to calculate the effective Federal Funds Rate to using the median.

[26] These uncollateralized loans are assumed to have zero credit risk in the model.

while collateralized borrowing does not, leverage constrained investors are willing to pay a higher rate for uncollateralized loans. The difference between uncollateralized and collateralized interest rates is equal to the Lagrange multiplier on the leverage constraint and hence naturally proxies for the shadow cost of this constraint.

Denote the economy-wide Lagrange multiplier as λ_t, Garleanu and Pedersen (2011) demonstrate that the shadow cost of leverage constraint flattens the security market line:

$$\mu_{it} - r_{ft} = \beta_{it}\gamma_t + \lambda_t m_{it}, \tag{10}$$

where β_{it} is the consumption risk exposure of asset i and γ_t is the consumption risk premium.

The theoretical insight in Eq. (10) can be readily applied to understand the performance shortfall of leverage funds relative to the benchmark index. Similar to Frazzini and Pedersen (2014), for simplicity we assume the margin requirement per dollar investment in a leverage fund is the same as that in its underlying index. Given that the leverage fund returns r_{it} are δ times the benchmark return b_{jt}, we have $\beta_{it} = \delta\beta_{jt}$. Substituting the expected returns for r_{it} and b_{jt} in the following equations into Eq. (1)

$$E\left[r_i - r_f\right] = \beta_{it}\gamma_t + \lambda_t m_t \tag{11}$$

$$E\left[b_j - r_f\right] = \beta_{jt}\gamma_t + \lambda_t m_t. \tag{12}$$

We get $E\left[\alpha_i\right] = \left(1-\delta\right) r_{ft} + \left(1-\delta\right)\lambda_t m_t$,or equivalently

$$r^c = \frac{E\left[\alpha_i\right]}{\left(1-\delta\right)} = r_{ft} + \lambda_t m_t. \tag{13}$$

Eq. (13) delivers the economic interpretation of our cost of leverage measure defined in Eq. (5): r^c captures both the prevailing risk-free rate and the shadow cost of leverage constraints. The second term in Eq. (13) arises because while per-dollar investments in the leveraged fund and the underlying index have the same margin requirement, the former provides δ times the risk exposure of the latter. Consequently, for the per dollar *risk exposure*, the margin requirement for investments in the leveraged fund is only $\frac{1}{\delta}$ of that for investments in the underlying index.

We then define our spread measure as $\psi \equiv r^c - r_f$, the difference between our cost of leverage measure and the risk-free rate, which is designed to capture $\lambda_t m_t$ in Eq. (13).[27]

[27] Jylha (2018) reports that the initial margin requirement for U.S. stocks under Regulation T has remained

Therefore, ψ is analogous to the interest-rate spread between the uncollateralized and collateralized rates modeled in Garleanu and Pedersen (2011): it is the shadow cost of investors' funding constraints. We now turn to empirically test whether our spread measure indeed captures such shadow cost of leverage constraints.

4. Data and Empirical Estimates

4.1. Data

Our sample period starts in June of 2006 when the first leveraged ETF is offered and ends in December of 2016. For our research purpose, we start by constructing a comprehensive dataset including all leveraged funds, dead or alive, that track a constant multiple of the daily performance of an underlying benchmark index. We rely primarily on the the Center for Research in Security Prices US Survivor-Bias-Free Mutual Fund Database (CRSP MFDB) to construct this list because it includes dead funds and thus is free of survivorship bias. We complement it with an alternative list of leveraged funds retrieved from Bloomberg, because neither CRSP MFDB nor Bloomberg provide a direct identifier for leveraged funds.[28] In our Data Appendix, we provide the step-by-step description of how we construct the comprehensive list of daily leveraged funds.

We obtain most of the fund-level information, such as fund returns, total net assets, and expense ratios from CRSP MFDB. We manually collect the historical leverage multiple and the name for the underlying index via Bloomberg and SEC filings. We obtain daily returns on the underlying index from Bloomberg.[29] To ensure the accuracy of the funding costs we compute, we focus on a final list of 678 domestic funds that track clearly defined and tradable spot indexes, representing a total of 625,088 fund-day observations between 2006 and 2016.[30]

unchanged since ends in January 1974, so ψ predominantly captures the variation in λ during our sample period.

[28]Applying our algorithm described in the Data Appendix on CRSP MFDB identifies almost all leveraged funds. Augmenting the CRSP leveraged funds list with the Bloomberg list expands the sample by 2%. In contrast, the Bloomberg list misses around one third of the leveraged fund names in the CRSP list. The coverage difference arises mainly because CRSP MFDB has historical data on dead funds, whereas Bloomberg does not always keep data for dead funds.

[29]Since returns on total return swaps and futures are typically adjusted for the dividends, we use the total returns on the underlying indexes (Vanguard (2013)).

[30]Using domestic funds avoids the issue of trading nonsynchronicity between the leveraged funds and the underlying. Clearly defined and tradable spot indexes are needed to back out the embedded funding cost.

Panels A and B of Figure 4 shows the number of funds and the exposure value across leverage levels over time for our final dataset. 2X (-2X) are the most popular leverage levels for bullish (bearish) funds for most of the sample period based on the number of funds. 3X (-3X) funds show up in late 2009 and the number of 3X (-3X) has grown to be about 40.0% (41.5%) of the number of 2X (-2X) funds.

Since our leverage funds dataset is new to the literature, we report detailed summary statistics of the variables used to construct our cost of leverage measure in the next subsection.

4.2. Data Description

Panel A of Table 1 reports the summary statistics of the variables used to compute α_{it} in Eq. (1) across leverage levels. The column labeled "$\overline{ExpRatio_{it}}$" reports the cross-sectional average of the times-series mean of the expense ratios for funds within a leverage level (δ). The average expense ratio ranges from 0.95% per annum to 2.05% per annum. 3X (-3X) funds have the lowest average expense ratios because they are mostly ETFs offered by Proshares and Direxion that charge lower fees. Column "$\overline{\sigma_i\left(ExpRatio_{it}\right)}$" reports the cross-sectional mean of the daily standard deviation of the expense ratio. The average standard deviation of the expense ratio is about two orders of magnitude smaller than the average expense ratio.[31] For example, 2X funds on average have an expense ratio of 1.34 per annum with a standard deviation of 0.02% per annum.

The rest of Panel A of Table 1 examines whether leveraged funds achieve the target multiple of the benchmark's performance at the daily frequency. Column "$\overline{\hat{\delta}_i}$" reports the cross-sectional average of the ordinary least squares (OLS) regression betas from regressing the daily fund returns on the daily benchmark returns. We find that the average OLS beta is equal to the target leverage multiple up to the second decimal place across target leverage levels, with the only exception that -3X funds have an average OLS beta of -3.01. Column "$\sigma\left(\hat{\delta}_i\right)$" shows that the cross-sectional standard deviation (within each target leverage multiple) of these OLS betas is small, with the numbers ranging between 0.003 for 1.5X funds and 0.06 for -3X funds. Therefore, on average leveraged funds manage to achieve the target multiple on a daily basis.

The next column reports the cross-sectional average of $R_i^2 \equiv \frac{V(r_{it})-V(\alpha_{it})}{V(r_{it})}$, which measures how much variation in daily fund returns can be explained by the underlying index times the

[31]Since the expense ratio is stable, for days with missing expense ratios we assume the expense ratio does not change.

target multiple. Consistent with the finding that leveraged funds on average achieve their target leverage level on a daily basis, we find the average R^2s ranging between 99.67% for -1X funds and 99.93% for 1.5X funds.

4.3. *Empirical estimates for cost of leverage and the shadow cost of leverage constraints*

This subsection demonstrates that our aggregate cost of leverage measure r^c tracks the benchmark risk-free rates and our shadow cost measure ψ is correlated with the TED spread during the financial crisis.

Figure 1 illustrates the time series relation between r^c and the two benchmark risk-free rates (the GC repo rate and the one-month T-bill rate) by plotting their three-month moving averages.[32] Our aggregate cost of leverage measure r^c fluctuates around the levels of the benchmark risk-free rates, consistent with the notion that r^c is a cost of leverage measure. For example, when the Federal Open Market Committee (FOMC) cut the fed funds rate to combat the financial crisis from 2007 to 2009, we observe that r^c declines in tandem.

While r^c is generally above the GC repo rate and the one-month T-bill rate, r^c can be more than 50 basis points below the two risk-free rates, in particular during the 2007–2009 financial crisis. This can be seen more easily in Sub-figure (a) of Figure 2, where we plot the three-month moving average of our shadow cost estimate:[33]

$$\psi_t = r_t^c - r_t^{GC\ repo}. \tag{14}$$

The negative ψ during the crisis is largely due to the elevated security lending fees associated with aggressive short selling between 2007 and 2009. We thus compute the shadow cost measure using the cost of leverage after adjusting for security lending fees (Eq. (6)),

$$\psi_t^{\text{adj}} = r_t^{c,\text{adj}} - r_t^{GC\ repo}, \tag{15}$$

Sub-figure (b) of Figure 2 shows that the three-month moving average of ψ_t^{adj} is almost

[32]Throughout the paper, all interest rates and interest-rate spreads are measured in percentage points per annum. We use 252 trading days to annualize daily returns.

[33]The GC repo rate corresponds to the collateralized risk-free rate featured in Garleanu and Pedersen (2011). Alternatively, we can use the EFFR or the one-month T-bill rate as the benchmark risk-free rate. In our online appendix, we show that our results are similar when using these two alternative benchmark risk-free rates.

always positive. To illustrate how the security lending income lowers the effective cost of leverage, the same figure also shows the three-month moving average of $\psi_t - \psi_t^{\text{adj}} = r_t^c - r_t^{c,\text{adj}}$. We observe that the effective cost of leverage was reduced by as much as 2.9 percentage points by the security lending income during the crisis, and this effect is minimal after the crisis. When we overlay ψ_t^{adj} with the TED spread, we observe that both ψ_t^{adj} and the TED spread spike during the 2007–2009 financial crisis, exhibiting strong comovement.

We report the summary statistics for r^c, the benchmark short-term risk-free rates, our spread measures of the shadow cost, and the TED spread in Panel B of Table 1. From June 2006 to December 2016, on average, r^c is about 0.24% per annum higher than the EFFR, 0.30% higher than the GC repo rate, and 0.44% higher than the one-month T-bill rate. The corresponding differences in medians are 0.63%, 0.63%, and 0.70%, respectively. These numbers indicate that on average leveraged funds borrow at a rate higher than the overnight uncollateralized borrowing rate for depository institutions (EFFR), which is in turn higher than the overnight collateralized borrowing rate (GC repo rate) and the U.S. government funding cost (one-month T-bill rate). Our baseline shadow cost estimate has mean and median values at 0.30% and 0.22%. Adjusting for the security lending income, our shadow cost estimate has mean and median values at 0.51% and 0.34%, respectively, similar to those of the TED spread.

The daily standard deviation of r^c is 3.9% per annum, much lower than those of α_{it}, suggesting taking the cross-sectional median reduces the impact of idiosyncratic noise at the fund level. However, the maximum and minimum values for the daily r^c are still quite extreme and its 25^{th} percentile value is negative. We thus take the monthly average value of r^c to further reduce the impact of measurement errors. We find that the monthly r^c has maximum and minimum values of 7.11 and -1.07%, respectively, and its 25^{th} percentile is positive at 0.49%. Furthermore, the first-order autoregressive (AR1) coefficient of the monthly r^c is 0.87 (as opposed to -0.03 for the daily r^c), in line with the persistence of benchmark interest rates. Similarly, we use moving averages of our shadow cost measures to reduce the impact of measurement errors.[34]

[34] We expect the noise in our measure to attenuate our results. Thus, techniques that reduce the impact of measurement errors will increase our test power.

5. Shadow cost estimates and binding leverage constraints

To investigate whether our spread measure ψ captures the shadow cost of leverage constraints, we start by examining whether ψ is higher in periods when the leverage constraints are likely more binding. We separate months into high, middle, and low states based on the 10^{th} and 90^{th} percentiles of the 36-month cumulative market return (MKT3Y, Cooper, Gutierrez, and Hameed (2004)) and VIX, respectively. Theories featuring an equity constraint such as He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) predict that the constraint is more binding when market participants suffer a large loss. Theories featuring a debt constraint such as Brunnermeier (2009); Adrian and Shin (2013) predict that the constraint is more binding when market volatility increases. Therefore, we expect the shadow cost estimate to be highest in the low state of MKT3Y and the high state of VIX.

Panel A of Table 2 shows that, after adjusting for the security lending income, our shadow cost estimate is on average highest in months with below 10^{th} percentile of MKT3Y. ψ^{adj} averages 0.95% in the low MKT3Y state versus 0.38% and 0.50% in the middle and high states, respectively.[35] It is interesting to note that our shadow cost estimate is higher in the high market state than in the middle market state. Theories typically predict the leverage constraint to be more binding in bear markets, but these theories are ambiguous regarding the tightness of leverage constraints in bull markets. This is expected because both demand for and supply of leverage can increase in bull markets, and depending on which one dominates, the leverage constraint can be tighter or looser compared to the middle market state. For comparison, Panel A of Table 2 also presents the monthly average for alternative funding condition proxies used in prior studies. We find that their relation with the market states are also not always monotonic.[36] The LEV measure of Adrian, Etula, and Muir (2014) (the leverage of security broker-dealers) and the MD measure in Asness et al. (2016) (the ratio of the margin debt over the total market capitalization for NYSE stocks) have the lowest value in the low market state, but they have the highest value in the middle state. The LCT measure in Boguth and Simutin (2018) (the innovations to the aggregate active mutual funds market beta) has the lowest value in the high state and the highest value in the middle

[35] ψ has the lowest average value in the low MKT3Y state because the security lending income is high during these months, as the large difference between ψ and ψ^{adj} in the low state suggests the security lending incomes lowers the effective funding cost by -0.88%.

[36] All these measures other than the TED spread are AR(1) innovations.

state. On the other hand, the TED spread used in Frazzini and Pedersen (2014) and the ICR measure in He, Kelly, and Manela (2017) (the AR(1) innovations to the intermediary capital ratio) increases and decreases monotonically from the low state to the high state, respectively.

In contrast, Panel B of Table 2 shows that the relation between these proxies and market states based on VIX is more monotonic. Our shadow cost measure, ψ^{adj}, and all the existing funding condition measures, except for the LCT measure, suggest that leverage constraints are more binding when the VIX is high and vice versa. These results are not contradictory to the results based on MKT3Y because volatility can be high during bull markets.

Overall, our results in Table 2 indicate that both our shadow cost measure and the TED spread comply with the intuition that the leverage constraints are more binding when market participants suffer large losses and when the volatility is high. However, the increase in funding costs could simply due to an increase in credit risk rather than a tighter leverage constraint. We conduct a sharper test of hypothesis (i) by examining changes in ψ upon quarter-ends. There is an extensive literature on financial intermediaries shrinking balance sheets on financial reporting days. If financial intermediaries are less willing to lend upon quarter-ends, we expect them to charge leveraged investors a higher financing rate even when the credit risk is unlikely to change.

We test this hypothesis in Panel A of Table 3 by running the following time series regressions:

$$y_t = c + \rho \times y_{t-1} + \beta \times \mathrm{QtrEnd}_t + \epsilon_t, \tag{16}$$

, where y_t are daily observations of ψ, ψ^{adj}, $\psi - \psi^{\mathrm{adj}}$, the TED spread, and the GC repo rate in regression specifications (1) through (5), respectively. QtrEnd is equal to one for the two trading days straddling quarter-ends, i.e., the last and the first trading days of a quarter. We control for the autocorrelation structure by adding the lagged dependent variable and report Newey and West (1987) t-statistics with 22 lags.

In regression specification (1), we find that the regression coefficient on QtrEnd is 1.31 (t-statistic = 4.5), indicating that the shadow cost of leverage constraints as captured by ψ is 131 basis points per annum higher at quarter-ends. Regression specification (2) shows that using ψ^{adj} rather than ψ yields quantitatively similar results. The regression coefficient is 1.36 and the t-statistic is marginally lower at 4.0. The similar results are expected because the security lending income is unlikely to change upon quarter-ends.[37] Regression specification (3) validates these interpretations by using $\psi - \psi^{adj}$ as the dependent variable. We find that $\psi - \psi^{adj}$ has an insignificant loading on QtrEnd of 0.06 (t-statistic = 0.25), indicating that the difference between ψ and ψ^{adj} contributes little to the increase in ψ upon quarter-ends.[38] To examine whether the results are driven by outliers, Panel B of Table 3 shows the average ψ on quarter-ends and non-quarter-end days year by year. We observe that ψ is higher upon quarter-ends for each of 10 years in our sample period with the only exception being 2009.

For comparison, regression specification (4) looks at the quarter-end change in the TED spread. The regression coefficient on QtrEnd is -0.01 with a t-statistic of -1.45, suggesting the quarter-end change in the TED spread is close to zero. These results are consistent with the recent studies that find substantial reduction in banks' repo borrowing but no detectable change in their borrowing rate upon quarter-ends (e.g. Munyan (2017)). Results in regression specification (5) show that the GC repo rate increases by only two basis points upon quarter-ends, confirming that the increase in ψ is not due to changes in the benchmark risk-free rate.

Overall, the significant increase in ψ and the lack of movement in TED spread upon quarter-ends indicate that financial intermediaries leave money on the table. This is consistent with the interpretation in Du, Tepper, and Verdelhan (2018), who find the violation of covered interest rate parity is more pronounced when financial contracts straddle quarter-ends, that financial intermediaries face a shadow cost of capital above their explicit borrowing cost such as the LIBOR rate. From this perspective, our results suggest that ψ better captures the equilibrium shadow cost of capital in the market than the TED spread.

6. Relation to BAB returns

Next, we use our spread measure ψ to test the key hypothesis in leverage-constraint based asset pricing theories—the flatness of the security market line is associated with the shadow cost of leverage constraints (e.g., Garleanu and Pedersen (2011); Frazzini and Pedersen

[37]Furthermore, because we infer the security lending income using unlevered index fund returns, the adjustment introduces additional measurement errors and thus lowers the statistical significance.

[38]Similar to the results here, we find that while adjusting for the security lending income is important for assessing the level of our shadow cost estimate, all the other results in this paper are not affected by this adjustment in a significant way. To save space, we present these results as part of the robustness tests in the online appendix.

(2014)).[39]

Frazzini and Pedersen (2014) construct the betting-against-beta (BAB) portfolio to capture the flatness of the security market line and put forward two testable predictions: a) when leverage constraints are more binding, ceteris paribus, the BAB premium should be higher, and b) consequently, the contemporaneous BAB returns should be lower. Frazzini and Pedersen (2014) test these two prediction by using the TED spread as the proxy for the shadow cost of leverage constraints. They find results supporting prediction (b) but not prediction (a). When Jylha (2018) examines the interest-rate spread between the brokers' borrowing cost and the three-month T-bill rate between 1934 and 1975, he also finds that this interest-rate spread does not predict the flatness of the security market line. In contrast, several studies find that alternative proxies for leverage constraints strongly predict BAB returns (Asness, Frazzini, Gormsen, and Pedersen (2016); Boguth and Simutin (2018); Jylha (2018); Hedegaard (2018)), lending support to prediction (a).

These findings seem puzzling because Garleanu and Pedersen (2011) predict that the most direct measure of the shadow cost of leverage constraints should be an interest-rate spread. These findings are nevertheless consistent with the interpretation that the TED spread captures financial intermediaries' leverage constraints rather than the leverage constraints of the marginal investor holding high-beta stocks. We now use our spread measure ψ_t as a proxy for the shadow cost of leverage constraint and test predictions (a) and (b) in Frazzini and Pedersen (2014).

6.1. *Relation to future BAB returns*

Table 4 tests for the positive association between the shadow cost of leverage constraints (ψ) and the future BAB returns in. For ease of comparison, we follow the regression specifications in Boguth and Simutin (2018). We regress average monthly BAB returns over the next one, six, or 12 months on the lagged one-, six-, or 12-month moving average of ψ, respectively. To account for the serial correlation introduced by the overlapping observations, we follow Boguth and Simutin (2018) and compute Newey-West t-statistics with 12 lags.[40]

In Panel A of Table 4, we find that ψ predicts future BAB returns with the theoretically correct positive sign across all nine regression specifications. The coefficients on the one-month moving average of ψ in regressions (1) through (3) are similar, ranging between 0.86

[39] The idea that a flatter security market line is associated with leverage constraints traces back to Black (1972).

[40] In Online Appendix, we show that our main results are robust to using Hodrick (1992) 1B standard errors, which have better finite-sample properties under the null hypothesis of no return predictability.

for the 12-month forecasting horizon and 0.91 for the six-month forecasting horizon. This means that a one percentage point increase in ψ over the past month is associated with an increase in average monthly BAB premium of 0.86% for the next 12 months. The coefficients on the six-month moving averages of ψ range between 2.77 for the six-month forecasting horizon and 3.10 for the one-month forecasting horizon. The coefficients on the 12-month moving averages of ψ range between 3.24 and 3.52. The economic interpretation is that if ψ increases by one percentage point over the past six (12) months, the average monthly BAB premium over the next 12 month will increase by 0.48% (0.27%).[41] The regression coefficients across the nine specifications are all statistically significant at 5% level with t-statistics ranging from 2.26 to 3.83, except for using one-month ψ to predict one-month BAB returns.[42]

Similar to the findings in Boguth and Simutin (2018), we find that the R^2 increases substantially when forecasting BAB returns over a longer horizon. For example, when using the six-month moving average of ψ as the predictor, the adjusted R^2's range from 7 for predicting the average BAB returns in the next month to 47 for predicting the average BAB returns in the next 12 months. In Panel B of Table 4 we demonstrate that the positive association between ψ and the future BAB returns is robust to using the spread measure with the EFFR as the benchmark risk-free rate (ψ^{EFFR}).

We then examine whether the predictive power of ψ is distinct from that of existing predictors for BAB returns. In Panel C of Table 4, we control for the TED spread in Frazzini and Pedersen (2014), the LCT measure in Boguth and Simutin (2018), which is the market beta of the aggregate stock portfolios held by actively managed mutual funds, and the MD measure in Asness, Frazzini, Gormsen, and Pedersen (2016), which is the amount of margin debt held against NYSE stocks as a percentage of the total market capitalization of NYSE stocks. For brevity, we focus on the six-month moving averages of ψ and the LCT measure.[43] Specifications (1) to (3) run bivariate regressions of the average monthly BAB returns over the next one, six, or 12 months on ψ and the TED spread. We find that the TED spread predicts BAB returns with a negative coefficient across all three specifications, consistent with the findings in Frazzini and Pedersen (2014). The coefficients are statistically

[41] To gauge the effect of a one percentage point cumulative change in ψ over the past six (12) months on future BAB returns, one should divide the coefficients on the six- (12-) month moving averages by six (12).

[42] Using moving averages to smooth out the noise in the one-month ψ increases the predictive power, as both the six- and 12-month moving averages of ψ predict one-month BAB returns significantly at the 5% level.

[43] Both the TED spread and the MD measure are very persistent. Following the original papers, we do not take the moving averages.

significant at the 5% level for the one- and six-month forecasting horizons, but insignificant for the 12-month forecasting horizon. After controlling for the TED spread, the coefficients on ψ are smaller than those of the univariate regression results in Panel A of Table 4, but remain economically and statistically significant at 1.70 (t-statistic = 2.10), 1.66 (t-statistic = 3.90), and 2.02 (t-statistic = 3.29) for predicting BAB returns in the next one, six, and 12 months, respectively. The positive predictive coefficient on ψ and the negative predictive coefficient on the TED spread in bivariate regressions (1) to (3) indicate that ψ is a better proxy for the shadow cost of leverage constraints formulated in Frazzini and Pedersen's prediction (a).

Next, specifications (4), (5), and (6) control for the LCT measure in Boguth and Simutin (2018) rather than the TED spread. Boguth and Simutin (2018) find that the LCT measure positively and strongly predicts future BAB returns in their sample period. In contrast, in our sample period, when controlling for ψ, the LCT measure predicts future BAB returns with a negative coefficient that is statistically insignificant across all three specifications. More importantly, we find that controlling for the LCT measure does not affect the coefficients on ψ. The coefficients on ψ are 3.01 (t-statistic = 2.49), 2.39 (t-statistic = 3.81), and 2.48 (t-statistic = 2.76) for predicting BAB returns in the next one, six, and 12 months, respectively, similar to those in the univariate regressions.

Finally, specifications (7), (8), and (9) control for the MD measure in Asness, Frazzini, Gormsen, and Pedersen (2016). Asness, Frazzini, Gormsen, and Pedersen (2016) find margin debt negatively predicts BAB returns and interpret low margin debt as indicating tighter leverage constraints. Consistent with their findings, the bivariate regressions from (7) through (9) show that the MD measure negatively predicts BAB returns in the next one, six, and 12 months, although the coefficient is only significant for the one-month forecasting horizon. Interestingly, for the one-month forecasting horizon, controlling for the MD measure increases the coefficient on ψ by one third. The coefficients on ψ are 4.80 (t-statistic = 3.63), 3.14 (t-statistic = 5.32), and 3.11 (t-statistic = 3.57) for the one-, six-, and 12-month forecasting horizons, respectively, each of which remains positive and highly significant.

6.2. *Relation to contemporaneous BAB returns*

In Table 5, we test for the negative association between the shadow cost of leverage constraints (ψ) and contemporaneous BAB returns in Frazzini and Pedersen's prediction (b). Because an increase in the expected returns of BAB depresses the realized returns of BAB in the same period but raises the realized returns of BAB in the subsequent periods, we use daily data to increase the power of detecting this negative contemporaneous correlation. To avoid the errors-in-variables problem due to the noise in daily ψ, we use the daily ψ as the dependent variable and daily BAB returns as the independent variable. Following Frazzini and Pedersen (2014), we control for the BAB's ex post exposure to the market excess return in the regressions. In regression specification (1), we regress the daily ψ on contemporaneous BAB returns and market excess returns. We find that the regression coefficient on BAB returns is -0.79 and the Newey-West t-statistic with 22 lags is -3.21. This means a one percentage point decrease in daily BAB returns is associated with a 0.79 percentage point increase in our annualized shadow cost measure.

In regression specification (2), we control for potential serial correlations by adding the lagged dependent variable to specification (1) and find little change in the negative contemporaneous relation between ψ and BAB returns. We additionally control for the change in the TED spread in specification (3), because Frazzini and Pedersen (2014) find it to be negatively correlated with the contemporaneous BAB returns. We find that controlling for the change in the TED spread slightly strengthens the negative contemporaneous relation between ψ and BAB returns as the coefficient on BAB returns is -0.86 with a t-statistic of -3.80. In specification (4), rather than controlling for the change in the TED spread, we control for the volatility risk by including changes in the daily VIX. The negative contemporaneous relation between ψ and BAB returns again survives controlling for the volatility risk. In specification (5), we simultaneously control for the change in the TED spread, the change in VIX, the market excess return, and the lagged ψ, and we find that the contemporaneous correlation between ψ and BAB returns remains negative and statistically significant.

Overall, our findings of a negative association between ψ and contemporaneous BAB returns and a positive association between ψ and future BAB returns support the theoretical predictions in Frazzini and Pedersen (2014). These results lend further support to the validity of using ψ as a proxy for the shadow cost of leverage constraints.

7. Supply and demand shifts in the leverage market

In this section, we combine our shadow cost measure (ψ) and the LCT measure in Boguth and Simutin (2018) to form a leverage price-quantity pair that identifies the demand and supply shifts in the leverage market. We argue that this demand-and-supply perspective is crucial for understanding empirical patterns associated with the leverage constraints. In particular, the demand-and-supply analysis predicts that the relation between the LCT measure and the BAB premium should be time varying.

The LCT measure is the market beta of the aggregate stock holdings of all active mutual funds (hereafter, LCT $\left(\beta_{MF}^{MKT}\right)$). As Boguth and Simutin (2018) highlight, because mutual funds face regulatory or self-imposed leverage constraints, they are willing to accept a lower risk-adjusted returns on high-beta stocks in exchange for the implicit leverage. Boguth and Simutin (2018) posit that LCT $\left(\beta_{MF}^{MKT}\right)$ is a contender to the TED spread as a proxy for leverage constraint tightness and hence LCT $\left(\beta_{MF}^{MKT}\right)$ should be positively correlated with the BAB premium. In contrast to this view, our interpretation is that mutual funds choose the optimal implicit leverage (their portfolio's market beta) given the shadow cost of the leverage constraints (which give rises to the BAB premium). Therefore, the LCT $\left(\beta_{MF}^{MKT}\right)$ measure captures the equilibrium quantity of leverage chosen by mutual fund managers. Depending on whether the demand or supply shift is the driving force in the leverage market, the correlation between the quantity of leverage $\left(\beta_{MF}^{MKT}\right)$ and the cost of leverage (the BAB premium) can be positive or negative.[44]

To test this prediction, we start by extending the results in Boguth and Simutin (2018) to December 2016 by using LCT $\left(\beta_{MF}^{MKT}\right)$ to predict average BAB returns over the next one, six, and 12 months.[45] We find that the LCT measure predicts BAB returns with a positive and significant coefficient between 1980 and 2016. For example, the six-month moving average of LCT predicts the average BAB returns over the next one, six, and 12 months with coefficients of 4.74 (t-statistic = 1.72), 5.81 (t-statistic = 2.47), and 7.15 (t-statistic = 3.56), respectively.

Panel B of Table 6 shows the same regression results in our sample period between July 2006 and December 2016. In contrast to the full sample results, the LCT measure predicts BAB returns with a negative coefficient across all nine specifications, except for a positive and insignificant coefficient when using one-month LCT to predict one-month BAB. For instance, when using the six-month moving average of LCT to predict average BAB returns in the next one, six, and 12 months, the predictive coefficients are −13.58 (t-statistic = −1.51), −15.24 (t-statistic = −1.76), and −16.26 (t-statistic = −2.55), respectively.[46]

The sign of the predictive coefficient on the LCT $\left(\beta_{MF}^{MKT}\right)$ measure switching from positive to negative is not surprising, according to the demand-and-supply explanation, if the

[44] A standard demand-and-supply analysis predicts that an outward shift in the supply (demand) of leverage will increase (decrease) the quantity of equilibrium leverage and decrease (increase) the cost of leverage.

[45] We splice the authors' original LCT measure, which is available from 1980 through 2014, with our replicated LCT from 2015 through 2016. In the period from 1980 to 2014, our replicated LCT has a 0.97 correlation with the original LCT. The details of the replication are in our Data Appendix.

[46] In untabulated results, we verify that the regression coefficients are positive when we use data before July 2006.

supply shift is more dominant in the leverage market in our sample period. To test this conjecture, we use our spread measure of the shadow cost of leverage constraints (ψ) and the LCT $\left(\beta_{MF}^{MKT}\right)$ measure to form a leverage price-quantity pair to identify demand- and supply-shifts. That is, positive (negative) co-movement between ψ and LCT $\left(\beta_{MF}^{MKT}\right)$ indicates that demand (supply) shifts are the dominant force.

We first look at the overall unconditional correlations between ψ and LCT $\left(\beta_{MF}^{MKT}\right)$. The Spearman rank correlation is -0.09 and the Pearson correlation is -0.05, consistent with the supply-shift channel being on average more important in our sample period. However, neither of the unconditional correlations is statistically significant.[47] More tellingly, Figure 5 looks at how LCT $\left(\beta_{MF}^{MKT}\right)$'s predictive power for future BAB returns changes with the conditional correlations between ψ and LCT $\left(\beta_{MF}^{MKT}\right)$. Specifically, at the end of each month between June 2009 to December 2016, we use the data in the past three years to compute the rolling correlations between the innovations in monthly ψ and LCT $\left(\beta_{MF}^{MKT}\right)$ in the top panel.[48] In the bottom panel, we then look at the predictive coefficient on LCT $\left(\beta_{MF}^{MKT}\right)$ from regressing the average monthly BAB returns in the next six months on the six-month moving average of LCT $\left(\beta_{MF}^{MKT}\right)$ over the same three year window.[49] We find interesting comovement between the rolling correlations and the rolling predictive coefficients. When the rolling correlation between ψ and LCT $\left(\beta_{MF}^{MKT}\right)$ becomes the most negative around 2010, indicating strong supply shifts, LCT $\left(\beta_{MF}^{MKT}\right)$ also predicts future BAB returns with the most negative coefficient. As the rolling correlation between ψ and LCT $\left(\beta_{MF}^{MKT}\right)$ becomes positive toward the end of 2016, LCT $\left(\beta_{MF}^{MKT}\right)$ also starts to predict the future BAB returns with a positive sign.[50]

Panel C of Table 6 formally tests the prediction that the time-varying relation between LCT $\left(\beta_{MF}^{MKT}\right)$ and future BAB returns is associated with supply-and-demand shifts in the leverage market. We define CoMove as the correlation between the innovations in LCT $\left(\beta_{MF}^{MKT}\right)$ and monthly ψ in the past 12 months. More positive CoMove indicates demand shifts are more important, and according to the demand-and-supply prediction, the relation between LCT $\left(\beta_{MF}^{MKT}\right)$ and future BAB premium should be more positive. Regres-

[47] The Spearman rank correlation has p-value 0.32, and the Pearson correlation has p-value 0.61.

[48] The innovations are computed using an AR(1) model with all data in the sample period.

[49] To give an example, in June 2010 we estimate the correlation using ψ and LCT between July 2007 and June 2010 (inclusive) and the predictive regression using the six-month moving averages of LCT that fall between July 2007 and June 2010 (inclusive), i.e., the first six-month moving average is computed between July 2007 and December 2007 and the last moving average is computed between January 2010 and June 2010.

[50] We plot one standard error confidence intervals in the figure, but these standard errors estimated in small samples need to be interpreted with caution.

sion specifications (1) through (3) regress the average BAB returns over the next one, six and 12 months on the 12-month moving average of LCT, CoMove computed in the same 12-month window, and their interaction term. We observe that the coefficients on the interaction term are positive and statistically significant at the 1% level across all three regression specifications. In regression specifications (4) through (6), we instead use an indicator variable (DemandShift = 1 if CoMove > 0, otherwise zero) to classify demand- and supply-shift dominant periods, we again find that a positive and significant coefficient at 1% level on the interaction term across the three forecasting horizons.

These results all point to a time-varying relation between LCT $\left(\beta_{MF}^{MKT}\right)$ and the BAB premium that is consistent with the demand-and-supply interpretation. This demand-and-supply interpretation also explains why ψ subsumes LCT $\left(\beta_{MF}^{MKT}\right)$ in predicting the BAB returns in Panel C of Table 4. This is because our spread measure ψ corresponds to the theoretically motivated interest-rate spread that captures the shadow cost of leverage constraints in Garleanu and Pedersen (2011). In contrast, LCT $\left(\beta_{MF}^{MKT}\right)$ is a measure of the quantity of leverage and hence its relation with the BAB premium can be either positive or negative. Overall, our evidence suggests that disentangling supply and demand shifts is crucial for interpreting the empirical patterns associated with leverage constraints.

8. Relation to the cross-section of stock returns

In this section, we use our shadow cost measure to test the theoretical prediction in Brunnermeier and Pedersen (2009) that the shadow cost of leverage constraints is an additional risk factor in the pricing kernel. States of the world with high shadow cost of leverage constraints are states when arbitragers' marginal utility of wealth is high. Consequently, stocks that pay off when the shadow cost is high are safe and should earn lower expected returns.

8.1. Preformation betas

We estimate the exposure of stock i to the time variation in the shadow cost of leverage constraints at the end of each month by running the following time series regression of excess stock returns on the market excess return (MKT) and the shocks to our shadow cost measure. We use daily observations available between the end of month $t-12$ and the end of month t to estimate betas for each stock and require at least 180 non-missing observations. The regression specification is

$$r_{i,d} = \beta_0 + \beta_i^{MKT} MKT_d + \beta_i^{\psi} \Delta\psi_d + \epsilon_{i,d} \tag{17}$$

, where r_{id}, MKT_d and $\Delta\psi_d$ are the daily stock excess returns, the daily market excess returns, and the daily ψ innovations at the close of day d.[51] To mitigate the impact of nonsynchronous trading and measurement errors in daily ψ, similar to Frazzini and Pedersen (2014), we use the 3-day moving average of these variables to estimate betas.

8.2. *Univariate Portfolio analysis*

We start the portfolio analysis with an univariate portfolio sort on β^{ψ}. At the end of each month t, all stocks in the given sample are sorted into quintile portfolios based on an ascending ordering of β^{ψ}. We then calculate the value-weighted average month $t+1$ excess return for each of the quintile portfolios, as well as for the zero-investment portfolio that is long the top quintile portfolio and short the bottom quintile portfolio ($5-1$ portfolio).[52] Our samples cover the months t from June 2007 through December 2016. This period is chosen because June 2007 and December 2016 are the first and last months for which we can estimate the regression in equation (17) with a full year's worth of data.

Panel A of Table 7 show the univariate portfolio sort results using all U.S.-based common stocks in the the Center for Research in Security Prices (CRSP) database that have a valid value of β^{ψ} at the end of each month t. We find that average excess returns are monotonically decreasing across the β^{ψ} quintiles. The bottom quintile portfolio generates an average excess return of 1.02% per month and the average excess return of the top quintile portfolio is 0.27% per month. The $5-1$ portfolio average return of -0.75% per month is economically large and statistically significant with a t-statistic of -2.3 after adjusting for heteroskedasticity and serial correlations following Newey and West (1987) with 12 lags.

To examine whether the pattern in the excess returns of the β^{ψ}-sorted portfolios is a manifestation of exposure to previously identified risk factors, we calculate the abnormal returns of the quintile portfolios relative to the CAPM, the CAPM plus BAB model (CAPM+BAB), the Fama and French (1993) model (FF3), the Carhart (1997) model (FFC), the Hou, Xue, and Zhang (2015) Q-factor model (Q), and the Fama and French (2015) model (FF5).[53] The

[51] To avoid look-ahead bias, we compute $\Delta\psi_d$ recursively using only data available up to day d. See the Data Appendix for more details.

[52] The excess stock return in month $t+1$ has been adjusted for the delisting returns in CRSP.

[53] The FF3 model includes the market (MKT) factor, the size (SMB, small minus big) and value (HML,

alphas exhibit a similar monotonically decreasing pattern across the quintiles. The $5-1$ portfolio generates monthly alpha of -0.88% per month (t-statistic $= -3.0$), -0.76% per month (t-statistic $= -2.3$), -0.78% (t-statistic $= -2.9$), -0.74% (t-statistic $= -2.8$), -0.75% (t-statistic $= -2.3$), and -0.67% (t-statistic $= -2.3$) relative to the CAPM, CAPM+BAB, FF3, FFC, Q, FF5 factor models, respectively. The alpha of the $5-1$ portfolio relative to each of the factor models is negative and statistically significant, demonstrating that standard risk factors do not explain the relation between β^{ψ} and average returns.

Panel A of Table 7 also reports the value-weighted pre-formation and post-formation β^{ψ} for each of the quintile portfolios. As emphasized in Ang, Hodrick, Xing, and Zhang (2006), "finding large spreads in the post-formation loadings is a very stringent requirement" in tests of a risk-based explanation that predicts contemporaneous relations between the true forward-looking factor loadings and expected returns. Because the true factor loadings are unobservable, researchers often implicitly assume that the portfolios sorted on the pre-formation sensitivities would have significant differential post-formation exposure to the proposed risk factor. We examine the validity of this assumption by computing the post-formation β^{ψ} from regressing the entire time series of post-formation portfolio daily excess returns on the contemporaneous MKT and innovations in ψ, as in Eq. (17). The results in Panel A of Table 7 indicate that the β^{ψ} $5-1$ portfolio has a strong positive post-formation sensitivity of 4.7, which is statistically significant at the 5% level. Thus, while the pre-formation β^{ψ} is an imperfect measure of the true factor loading, it is sufficiently accurate to generate economically and statistically significant post-formation exposure to ψ.[54]

In Panels B and C of 7, we repeat our analysis using the Liquid and Large Cap samples to distinguish between risk pricing and mispricing explanations because limits to arbitrage (Shleifer and Vishny (1997)) are less likely to bind in liquid and large stocks. The Liquid sample is the subset of the full sample with Amihud (2002) illiquidity (ILLIQ) values that are less than or equal to the 80th percentile month t ILLIQ value among NYSE stocks. The

high minus low) factors. The FFC model includes MKT, SMB, HML, and the momentum (MOM) factor. FF5 includes MKT, HML, the size (SMB_5), profitability (RMW, robust minus weak), and investment (CMA, conservative minus aggressive) factors.The Q model includes MKT, the size (ME) factor, the return-on-equity (ROE) factor, and the investment over asset (I/A) factor. We obtain MKT, SMB, HML, RMW, CMA factor returns from Kenneth French's online data library, the BAB returns from the AQR online data library, and the ME, ROE, I/A factor returns from Lu Zhang.

[54] When the proposed risk factor is not a traded return, the literature typically reports a lack of significant dispersion in post-formation sensitivities, likely due to measurement errors in pre-formation betas. See Ang, Hodrick, Xing, and Zhang (2006) and Lu and Murray (2017) for more discussions. Our portfolio sort approach tests for the rank correlation between pre-formation betas and future returns, and thus it is more robust to the measurement errors than tests of the linear relation between pre-formation betas and future returns.

Large Cap sample is the subset of the full sample with market capitalization (MKTCAP) values that are greater than or equal to the 50th percentile value of month t MKTCAP among NYSE stocks.

We find similar and significant patterns in excess returns, factor model alphas, and post-formation betas in the Liquid and Large Cap samples. The β^{ψ} $5-1$ excess returns are -0.76% (t-statistic $= -2.5$) and -0.60% (t-statistic $= -2.0$) in the Liquid and Large Cap samples, respectively. In the Liquid sample, the $5-1$ portfolio generates monthly alpha of -0.90% (t-statistic $= -3.5$), -0.79% (t-statistic $= -2.7$), -0.80% (t-statistic $= -3.2$), -0.75% (t-statistic $= -3.1$), -0.76% (t-statistic $= -2.5$), and -0.66% (t-statistic $= -2.2$) relative to the CAPM, CAPM+BAB, FF3, FFC, Q, and FF5 factor models, respectively. These numbers are slightly larger in magnitude compared with those of the All stocks sample. In the Large Cap sample, the $5-1$ portfolio generates monthly alpha of -0.74% (t-statistic $= -3.0$), -0.62% (t-statistic $= -2.1$), -0.63% (t-statistic $= -2.6$), -0.58% (t-statistic $= -2.6$), -0.60% (t-statistic $= -2.0$), and -0.47% (t-statistic $= -1.6$) relative to the CAPM, CAPM+BAB, FF3, FFC, Q, and FF5 factor models, respectively. The alphas in the Large Cap sample are smaller than those in the All Stocks sample but remain significant at 5% level, with the only exception being the marginally significant FF5 alphas. Finally, the β^{ψ} $5-1$ portfolios in both the Liquid and Large Cap samples exhibit significant post-formation β^{ψ} of 4.79 (t-statistic $= 2.7$) and 4.91 (t-statistic $= 2.9$), respectively.

Table 8 presents the same univariate portfolio sorting analysis based on β^{TED}, which is computed under the same regression specification in Eq. (17) except for replacing $\Delta\psi$ with ΔTED. In a sharp contrast with the pricing effect of β^{ψ}, we find no evidence that the exposure to the innovations in the TED spread is priced in the cross-section of stock returns. The β^{TED} $5-1$ excess returns are -0.17% (t-statistic $= -0.6$) and -0.15% (t-statistic $= -0.5$) and -0.12% (t-statistic $= -0.12$) in the Full, Liquid and Large Cap samples, respectively. Adjusting for exposures to standard factor models yields alphas that are positive and statistically insignificant.

8.3. Bivariate Portfolio Analyses

Having demonstrated a strong negative cross-sectional relation between β^{ψ} and expected stock returns that is not explained by standard risk factors, we move to investigate the possibility that this relation can be explained by exposure to the existing proxies for funding conditions. We compute the sensitivities of returns to these proxies and use them as the control variables. Table 9 reports the equal-weighted average sensitivities for each quintile portfolio. The results of the bivariate portfolio analyses with these control variables are shown in Table 10. Specifically, at the end of each month t, we first sort all stocks into quintiles based on the ascending values of a control variable, and then within each control variable quintile, we sort stocks into quintile portfolios based on an ascending ordering of β^{ψ}. We then calculate the value-weighted month $t+1$ excess return for each of the resulting portfolios. Next, we compute the average month $t+1$ excess return across the control variable quintile portfolios within each β^{ψ} quintile, and refer to this as the bivariate β^{ψ} quintile portfolio excess return. Finally, we calculate the difference in month $t+1$ returns between the bivariate β^{ψ} top and bottom quintile portfolios (bivariate β^{ψ} $5-1$ portfolio). Since the bivariate β^{ψ} quintile portfolios have similar values of the control variable, any return pattern across the bivariate β^{ψ} quintile portfolios is unlikely to be driven by the control variable.

We first control for sensitivities to innovations in the TED spread (β^{TED}). The 3-month LIBOR used to compute the TED spread has historically been considered as a measure of the funding cost for large commercial banks.[55] Table 9 reports the average β^{TED} across that β^{ψ} quintiles. We do not find a consistent relation between β^{TED} and β^{ψ} , consistent with our earlier results that the funding costs of leveraged funds and banks captured by ψ and the TED spread are quite different. Table 10 shows that controlling for β^{TED} does not appear to explain the negative relation between average returns and β^{ψ}. The bivariate β^{ψ} $5-1$ portfolio that is neutral to β^{TED} earns a monthly return spread of -0.58% (t-statistic $= -2.4$), CAPM alpha of -0.66% (t-statistic $= -3.2$), CAPM+BAB alpha of -0.59% (t-statistic $= -2.5$), FF3 alpha of -0.59% (t-statistic $= -3.1$), FFC alpha of -0.55% (t-statistic $= -3.3$), Q alpha of -0.58% (t-statistic $= -2.4$), and FF5 alpha of -0.51% (t-statistic $= -2.4$).

Next, we control for VIX beta (β^{VIX}). Ang et al. (2011) find that hedge fund leverage tends to decrease after VIX increases, suggesting links between leverage and VIX. Ang et al. (2006) find that expected stock returns are negatively related to VIX beta, measured as the slope coefficient on the change in the VIX index from a 1-month rolling window regression of daily excess stock returns on contemporaneous MKT and VIX changes. Table 9 shows that the average β^{VIX} tends to increase with β^{ψ} quintiles across the samples, suggesting stocks that perform poorly when VIX increases overlap with stocks that perform poorly when the shadow cost of leverage constraints increases. Therefore, controlling for β^{VIX} could

[55] A caveat is that the LIBOR rate may have been understated during the financial crisis due to manipulation.

potentially explain the negative relation between β^{ψ} and future stock returns. However, Table 10 shows that controlling for β^{VIX} only slightly reduces the excess returns on the β^{ψ} $5-1$ portfolio. The bivariate β^{ψ} $5-1$ portfolio that is neutral to β^{VIX} earns a monthly return spread of -0.68% (t-statistic $= -2.9$) as opposed to -0.75% in the univariate sorts. The risk adjusted returns all remain statistically significant, with CAPM alpha of -0.75% (t-statistic $= -3.6$), CAPM+BAB alpha of -0.67% (t-statistic $= -2.7$), FF3 alpha of -0.67% (t-statistic $= -3.3$), FF3 alpha of -0.64% (t-statistic $= -3.4$), Q alpha of -0.68% (t-statistic $= -2.9$), and FF5 alpha of -0.55% (t-statistic $= -2.6$).

Our next series of tests examine whether sensitivities to the existing leverage measures in the literature can explain the premium associated with β^{ψ}, which include β^{LCT} (Boguth and Simutin (2018)), β^{LEV}(Adrian, Etula, and Muir (2014)), and β^{ICR} (He, Kelly, and Manela (2017)).[56] Table 9 finds no general monotonic patterns of β^{LCT}, β^{LEV}, and β^{ICR} across β^{ψ} quintiles. These results are consistent with our discussions in Section 7 that leverage measures can be negatively or positively correlated with our cost of leverage measure depending on whether supply or demand shifts are driving the equilibrium. Table 10 finds little evidence that any of β^{LCT}, β^{LEV}, and β^{ICR} can explain the pricing effect of β^{ψ}. The average returns and all alphas of the bivariate β^{ψ} $5-1$ portfolios that are neutral to β^{LCT}, β^{LEV}, and β^{ICR} range from -0.57% per month to -0.85% per month in magnitude and are all statistically significant at the 1% level.

In the final column of Panel A in Table 10, we control for idiosyncratic volatility (IVOL), calculated as the standard deviation of the residuals from a 1-month rolling window regression of daily excess stock returns on MKT, SMB, and HML. Ang et al. (2006) find that IVOL is negatively related to the cross section of future stock returns. In Table 9, we see that stocks in both the bottom and top β^{ψ} quintiles have high IVOL. Therefore, we do not expect IVOL to explain the monotonically decreasing average returns across β^{ψ} sorted portfolios. In Table 9, we find that the average return and alphas of the bivariate β^{ψ} $5-1$ portfolio are slightly smaller in magnitude after controlling for IVOL, but they remain economically and statistically significant. The monthly return spread is -0.71% (t-statistic $= -3.0$), CAPM alpha is -0.77% (t-statistic $= -3.5$), CAPM+BAB alpha is -0.74% (t-statistic $= -3.4$), FF3 alpha is -0.70% (t-statistic $= -3.5$), FFC alpha is -0.70% (t-statistic $= -3.6$), Q alpha is -0.71% (t-statistic $= -3.0$), and FF5 alpha is -0.56% (t-statistic $= -2.5$).

Finally, in Panel B and C of in Table 10, we repeat our analysis using the Liquid and Large Cap samples, respectively. Confining the sample to liquid stocks decreases the excess

[56] Our Data Appendix describes the computation of these betas.

returns and alphas for the bivariate β^{ψ} $5-1$ portfolios controlling for β^{VIX}, β^{LCT}, β^{LEV}, and β^{ICR} and slightly increases the alphas for the bivariate β^{ψ} $5-1$ portfolios controlling for β^{TED} and IVOL. Importantly, the bivariate β^{ψ} $5-1$ portfolios still generate monthly excess returns and alphas that are significant at 5% level across all specifications. In the Large Cap sample, similar to the univariate sort results, excess returns and alphas are smaller in magnitude across the board. Nevertheless, the excess returns on the bivariate β^{ψ} $5-1$ portfolios remain economically large between -64 to -42 basis points per month. The bivariate β^{ψ} $5-1$ excess returns are statistically significant at the 5% level when controlling for β^{LCT}, β^{LEV}, β^{ICR} and IVOL and are significant at the 10% level when controlling for β^{TED} and β^{VIX}. Adjusting for risk exposures generally yield alphas that are significant at the 5% level, with exceptions being Q-factor alphas for the bivariate β^{ψ} $5-1$ portfolios controlling for β^{TED} (t-statistic $= -1.8$) and β^{VIX}(t-statistic $= -1.9$) and FF5 alphas for the bivariate β^{ψ} $5-1$ portfolios controlling for β^{TED} (t-statistic $= -1.9$), β^{VIX}(t-statistic $= -1.7$), and β^{LCT}(t-statistic $= -1.9$). Overall, our bivariate portfolio results show that the pricing effect of β^{ψ} is robust to controlling for exposure to the existing proxies for funding conditions.

8.4. *Risk exposure to the shadow cost of leverage constraints and BAB premium*

The leverage constraint model in Frazzini and Pedersen (2014) predicts that high-beta stocks have lower CAPM alphas because leverage constrained investors use high-beta stocks to achieve high risk exposure. In their model, the BAB premium is completely driven by $-\Delta\beta \times \lambda_t m_t$, i.e. the CAPM beta difference times the shadow cost of leverage constraints (see Eq. (10)).[57] With our new measure of the shadow cost of leverage constraints, we can quantitatively assess this prediction.

The difference in average CAPM alpha between the high and low CAPM beta portfolios in Table 3 of Frazzini and Pedersen (2014) is -0.62 per month. The corresponding difference in realized CAPM betas is 1.18. In order for the CAPM beta difference to fully account for the difference in CAPM alphas, we need to have $-\Delta\beta \times \lambda_t m_t = -0.62\%$. Given $\Delta\beta = 1.18$, the shadow cost of leverage constraints $\lambda_t m_t$ should be at least 0.5% per month. In contrast,

[57] Frazzini and Pedersen (2014) invite researchers to assess this prediction quantitatively, "An interesting topic for future research is to empirically estimate agents' leverage constraints and risk preferences and study whether the magnitude of the BAB returns is consistent with the model or should be viewed as a puzzle." Following their paper, the high and low CAPM beta stocks are assumed to have the same margin requirement.

according to our estimate using the monthly ψ in our shorter sample period, the shadow cost of leverage constraints is an order of magnitude smaller than 0.5% per month (or 6% per annum): ψ averages 0.30 per annum and has an interquartile of 0.36 per annum.

This contrast highlights that the leverage constraint model in Frazzini and Pedersen (2014) is meant to deliver theoretical insight rather than empirical realism. A natural extension of this model is to account for the fact that when the expected returns on an asset depends on the shadow cost of leverage constraints, this asset has risk exposure to the time-variation in the shadow cost of leverage constraints and hence should earn additional risk premium associated with this discount rate risk (Brunnermeier and Pedersen (2009)).

As documented in this section, this risk premium is quite substantial as the univariate β^{ψ} $5-1$ portfolio earns 0.75 per month with a FF5 alpha of 0.67 per month. To explore how much of BAB premium can be explained by the discount rate risk associated with the time-variation in the shadow cost of leverage constraints, we regress BAB returns on the returns of the univariate β^{ψ} $5-1$ portfolio. We find that BAB returns load negatively and significantly on the univariate β^{ψ} $5-1$ portfolio, consistent with the theoretical and empirical results that the BAB portfolio performs well when the shadow cost of leverage constraints is high.[58] The exposure to the univariate β^{ψ} $5-1$ portfolio explains nearly half of the BAB 's CAPM alpha, which is 0.36% per month but statistically insignificant in our sample period.

9. Conclusion

Using the most comprehensive dataset of daily leveraged funds known to the literature, we construct an alternative measure to the TED spread for estimating the shadow cost of leverage constraints. Leveraged funds provide a rare opportunity to infer the financing terms between leveraged institutional investors and major financial intermediaries in the market. Since leveraged funds' borrowing has very low credit risk, our shadow cost measure—the interest-rate spread between the market-wide cost of leverage for leveraged funds and a benchmark risk-free rate—closely resembles the theoretical construct of the shadow cost of leverage constraints in Garleanu and Pedersen (2011).

We uncover strong evidence in supportive of the leverage-constraint based asset pricing

[58]Specifically, we regress the monthly BAB returns on the contemporaneous univariate β^{ψ} $5-1$ portfolio returns and the market excess return. The coefficients on the intercept, the β^{ψ} $5-1$ portfolio returns, and the market excess return are 0.20 (Newey West t-statistics = 0.39), -0.19 (Newey West t-statistic = -2.1), and 0.00 (Newey West t-statistic = 0.03) , respectively.

theories using our shadow cost measure. We find our shadow cost measure spikes upon quarter-ends, positively predicts BAB premium, and negatively correlates with contemporaneous BAB returns. Furthermore, we find that innovations in our shadow cost measure are priced in the cross section of stock returns. Stocks that underperform when our measure indicates high shadow cost of leverage constraints on average earn 0.75% more per month. These time-series and cross-sectional patterns are all consistent with the theoretical predictions for a valid proxy for the shadow cost of leverage constraints. In contrast, these patterns except for the negative relation with contemporaneous BAB returns are not detected when using the TED spread as the shadow cost measure. Finally, we show that using our shadow cost measure helps to identify the non-monotonic relation between the tightness of leverage constraints and the level of implicit leverage used by active mutual funds, highlighting the importance of distinguishing between supply and demand shifts in the leverage market. We conclude that our shadow cost measure is a useful tool for assessing the wide-ranging asset pricing implications of leverage constraints.

References

Adrian, T., Etula, E., Muir, T., 2014. Financial Intermediaries and the Cross-Section of Asset Returns: Financial Intermediaries and the Cross-Section of Asset Returns. The Journal of Finance 69, 2557–2596.

Adrian, T., Shin, H. S., 2013. Procyclical Leverage and Value-at-Risk. Review of Financial Studies p. hht068.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Ang, A., Gorovyy, S., van Inwegen, G. B., 2011. Hedge fund leverage. Journal of Financial Economics 102, 102–126.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The Cross-Section of Volatility and Expected Returns. The Journal of Finance 61, 259–299.

Asness, C. S., Frazzini, A., Gormsen, N. J., Pedersen, L. H., 2016. Betting Against Correlation: Testing Theories of the Low-Risk Effect. SSRN Electronic Journal .

Asness, C. S., Moskowitz, T. J., Pedersen, L. H., 2013. Value and Momentum Everywhere. The Journal of Finance 68, 929–985.

Avellaneda, M., Zhang, S., 2010. Path-Dependence of Leveraged ETF Returns. SIAM Journal on Financial Mathematics 1, 586–603.

Black, F., 1972. Capital Market Equilibrium with Restricted Borrowing. The Journal of Business 45, 444–455.

Boguth, O., Simutin, M., 2018. Leverage constraints and asset prices: Insights from mutual fund risk taking. Journal of Financial Economics 127, 325–341.

Brunnermeier, M. K., 2009. Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic Perspectives 23, 77–100.

Brunnermeier, M. K., Nagel, S., Pedersen, L. H., 2008. Carry Trades and Currency Crashes. NBER Macroeconomics Annual 23, 313–348.

Brunnermeier, M. K., Pedersen, L. H., 2009. Market Liquidity and Funding Liquidity. Review of Financial Studies 22, 2201–2238.

Brunnermeier, M. K., Sannikov, Y., 2014. A Macroeconomic Model with a Financial Sector. American Economic Review 104, 379–421.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57–82.

Charupat, N., Miu, P., 2011. The pricing and performance of leveraged exchange-traded funds. Journal of Banking & Finance 35, 966–977.

Cheng, M., Madhavan, A., 2009. The Dynamics of Leveraged and Inverse-Exchange Traded Funds. SSRN Scholarly Paper ID 1393995, Social Science Research Network, Rochester, NY.

Cooper, M. J., Gutierrez, R. C., Hameed, A., 2004. Market states and momentum. The Journal of Finance 59, 1345–1365.

Cornett, M. M., McNutt, J. J., Strahan, P. E., Tehranian, H., 2011. Liquidity risk management and credit supply in the financial crisis. Journal of Financial Economics 101, 297–312.

Du, W., Tepper, A., Verdelhan, A., 2018. Deviations from Covered Interest Rate Parity: Deviations from Covered Interest Rate Parity. The Journal of Finance 73, 915–957.

Evans, R. B., 2010. Mutual Fund Incubation. The Journal of Finance 65, 1581–1611.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Frazzini, A., Pedersen, L., 2012. Embedded Leverage. Tech. Rep. w18558, National Bureau of Economic Research, Cambridge, MA.

Frazzini, A., Pedersen, L. H., 2014. Betting against beta. Journal of Financial Economics 111, 1–25.

Garleanu, N., Pedersen, L. H., 2011. Margin-based Asset Pricing and Deviations from the Law of One Price. Review of Financial Studies 24, 1980–2022.

He, Z., Kelly, B., Manela, A., 2017. Intermediary asset pricing: New evidence from many asset classes. Journal of Financial Economics 126, 1–35.

He, Z., Krishnamurthy, A., 2013. Intermediary Asset Pricing. American Economic Review 103, 732–770.

He, Z., Krishnamurthy, A., 2018. Intermediary Asset Pricing and the Financial Crisis. Annual Review of Financial Economics 10, 173–197.

Hedegaard, E., 2018. Time-Varying Leverage Demand and Predictability of Betting-Against-Beta. SSRN Scholarly Paper ID 3194626, Social Science Research Network, Rochester, NY.

Hodrick, R. J., 1992. Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement. The Review of Financial Studies 5, 357–386.

Hou, K., Xue, C., Zhang, L., 2015. Digesting Anomalies: An Investment Approach. The Review of Financial Studies 28, 650–705.

Ivanov, I., Lenkey, S., 2014. Are Concerns About Leveraged ETFs Overblown? SSRN Scholarly Paper ID 2544657, Social Science Research Network, Rochester, NY.

Jiang, W., Yan, H., 2016. Financial Innovation, Investor Behavior, and Arbitrage: Implications from the ETF Market. SSRN Scholarly Paper ID 2023142, Social Science Research Network, Rochester, NY.

Jylha, P., 2018. Margin Requirements and the Security Market Line. The Journal of Finance 73, 1281–1321.

Kisin, R., Manela, A., 2016. The Shadow Cost of Bank Capital Requirements. The Review of Financial Studies 29, 1780–1820.

Koijen, R. S. J., Yogo, M., 2016. Shadow Insurance. Econometrica 84, 1265–1287.

Lu, L., Wang, J., Zhang, G., 2009. Long Term Performance of Leveraged ETFs. SSRN Electronic Journal .

Lu, Z., Murray, S., 2017. Bear Beta. SSRN Scholarly Paper ID 2871737, Social Science Research Network, Rochester, NY.

Moskowitz, T. J., Ooi, Y. H., Pedersen, L. H., 2012. Time series momentum. Journal of Financial Economics 104, 228–250.

Munyan, B., 2017. Regulatory Arbitrage in Repo Markets. SSRN Scholarly Paper ID 2685592, Social Science Research Network, Rochester, NY.

Newey, W. K., West, K. D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703.

Shleifer, A., Vishny, R. W., 1997. The Limits of Arbitrage. The Journal of Finance 52, 35–55.

Tang, H., Xu, X. E., 2013. Solving the Return Deviation Conundrum of Leveraged Exchange-Traded Funds. Journal of Financial and Quantitative Analysis 48, 309–342.

Tuzun, T., 2014. Are Leveraged and Inverse ETFs the New Portfolio Insurers? SSRN Scholarly Paper ID 2190708, Social Science Research Network, Rochester, NY.

Vanguard, 2013. Understanding Synthetic ETFs.

Figure 1: Time Series of r^c

This figure shows the three-month moving averages of our cost of leverage measure (r^c), as defined in Eq (5), as well as the three-month moving averages of the benchmark risk-free rates: the one-month Treasury bill rate (T-bill 1M), and the general collateral repo rate (GC repo). The gray shaded area indicates the US recession from December 2007 to June 2009 defined by National Bureau of Economic Research (NBER), and the light blue shaded area indicates the Euro area recession from October 2011 to March 2013 defined by Center for Economic Policy Research (CEPR).

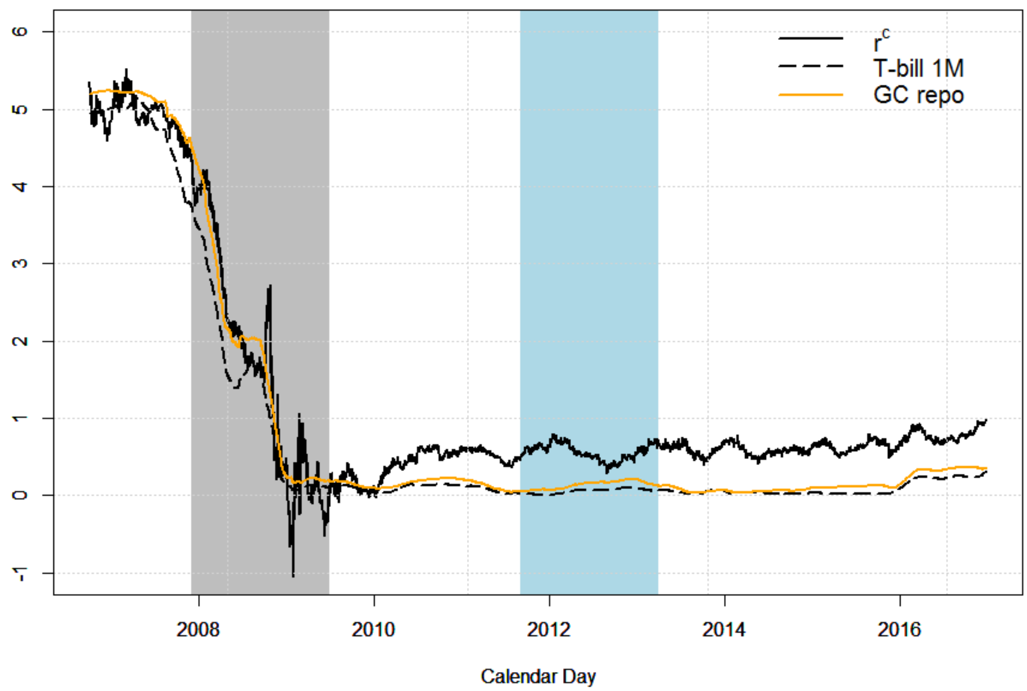
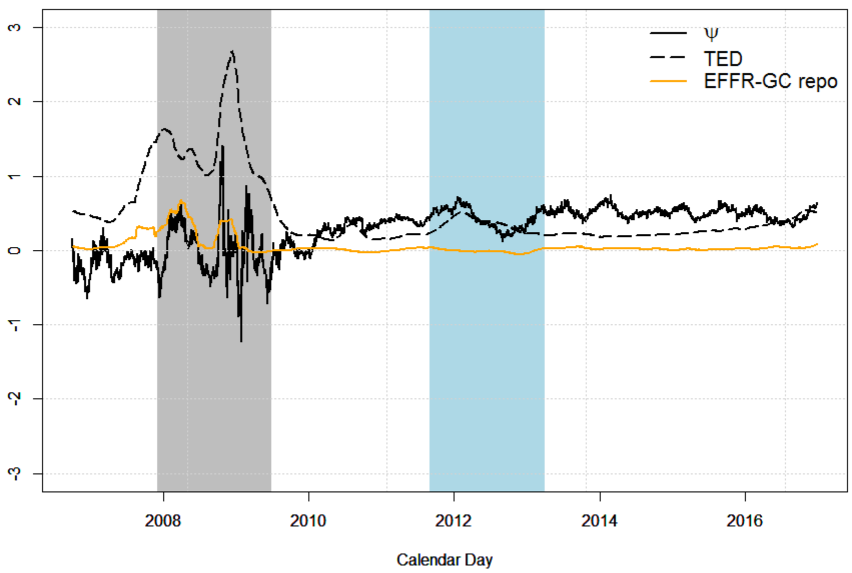


Figure 2: Time Series of ψ

Sub-figure (a) plots the three-month moving averages of our spread measure of the shadow cost of leverage constraints (ψ, the difference between r^c and the GC repo rate). The plot compares our spread with the three-month moving averages of the TED spread and the EFFR-GC repo spread. Sub-figure (b) plots the three-month moving averages of our spread measure after adjusting for the security lending income (ψ^{adj}, the difference between $r^{c,\text{adj}}$ and the GC repo rate), the TED spread, and the difference between ψ and ψ^{adj}. The gray shaded area indicates the US recession from December 2007 to June 2009 defined by National Bureau of Economic Research (NBER), and the light blue shaded area indicates the Euro area recession from October 2011 to March 2013 defined by Center for Economic Policy Research (CEPR).

(a) ψ and other funding spreads



(b) ψ^{adj},the TED spread, and $\psi - \psi^{\text{adj}}$

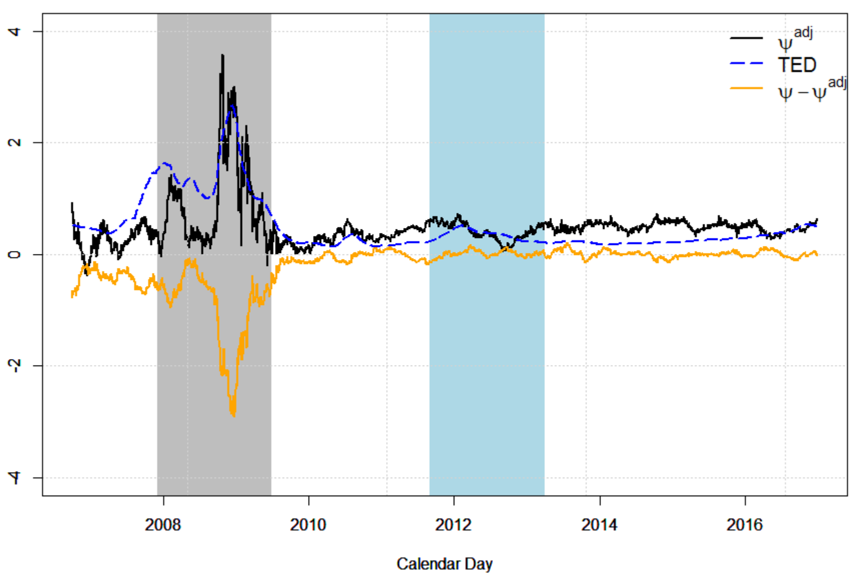


Figure 3: An Example

These figures illustrate a typical leveraged fund using the official web-page for ProShares Ultra Financials. Sub-figure (a) shows the overview of the fund and sub-figure (b) shows the fund holdings. The rows after the stock holding of JPMORGAN CHASE & CO are not shown to save space.

(a) Fund Overview

ProShares Ultra Financials seeks daily investment results, before fees and expenses, that correspond to two times (2x) the daily performance of the Dow Jones U.S. Financials^{SM} Index.

This leveraged ProShares ETF seeks a return that is 2x the return of an index or other benchmark (target) ***for a single day***, as measured from one NAV calculation to the next. Due to the compounding of daily returns, ProShares' returns over periods other than one day will likely differ in amount and possibly direction from the target return for the same period. These effects may be more pronounced in funds with larger or inverse multiples and in funds with volatile benchmarks. Investors should monitor their holdings consistent with their strategies, as frequently as daily. For more on correlation, leverage and other risks, please read the prospectus.

Considerations for Geared Investing – Learn More

Fund Snapshot

Ticker	UYG
Intraday Ticker	UYG.IV
CUSIP	74347X633
Inception Date	1/30/07
Expense Ratio *	0.95%

Price Information as of 7/24/18

NAV	$43.70
NAV Change	$0.08
Market Price Closing	$43.64
Market Price Closing Change	$0.05
Daily Trading Volume	102,834

(b) Fund Holdings

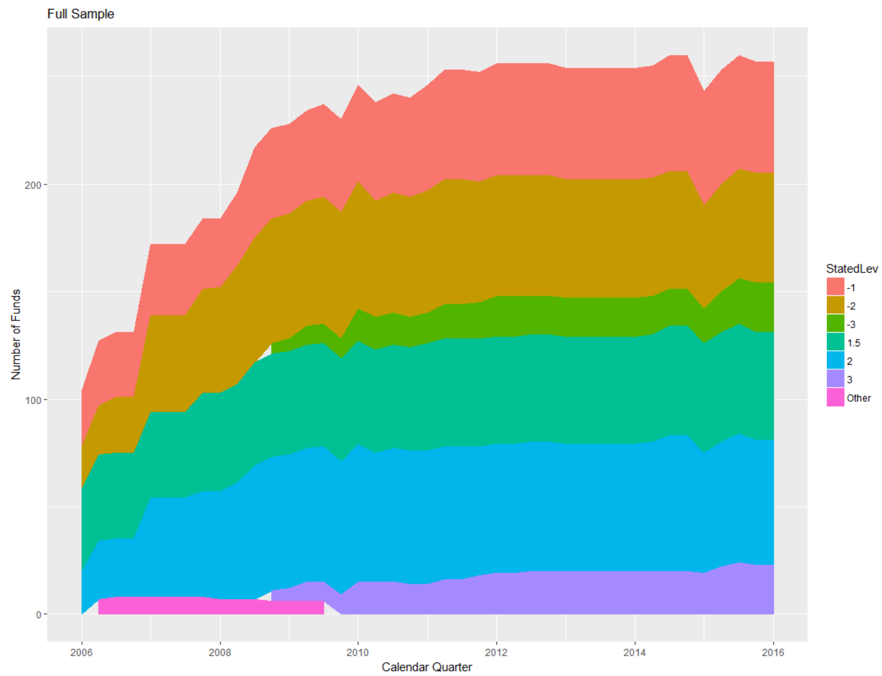
As of 7/24/18

Description	Ticker Symbol	Exposure Value (Notional + G/L)	Market Value ($)
DJ U.S. FINANCIALS INDEX SWAP UBS AG	-	329,268,315.66	-
DJ U.S. FINANCIALS INDEX SWAP DEUTSCHE BANK AG	-	263,219,753.41	-
ISHARES U.S. FINANCIALS (IYF) SWAP MORGAN STANLEY & CO. INTERNATIONAL PLC	-	152,522,542.78	-
DJ U.S. FINANCIALS INDEX SWAP BANK OF AMERICA NA	-	97,806,744.11	-
DJ U.S. FINANCIALS INDEX SWAP SOCIETE GENERALE	-	84,907,347.66	-
DJ U.S. FINANCIALS INDEX SWAP CITIBANK NA	-	68,070,619.21	-
DJ U.S. FINANCIALS INDEX SWAP GOLDMAN SACHS INTERNATIONAL	-	25,044,912.28	-
DJ U.S. FINANCIALS INDEX SWAP MORGAN STANLEY & CO. INTERNATIONAL PLC	-	14,375,357.74	-
ISHARES U.S. FINANCIALS (IYF) SWAP BANK OF AMERICA NA	-	12,637,592.40	-
DJ U.S. FINANCIALS INDEX SWAP CREDIT SUISSE INTERNATIONAL	-	2,439,593.18	-
JPMORGAN CHASE & CO	JPM	-	$55,499,501.70

Figure 4: Number of Funds in the Final Dataset (2006 - 2016)

Sub-figure (a) shows the number of funds and sub-figure (b) shows the total value of exposure in our final dataset across the stated leverage levels. These are domestic daily leveraged funds tracking spot indexes.

(a) Number of Funds in Final Dataset



(b) Exposure Value in Final Dataset

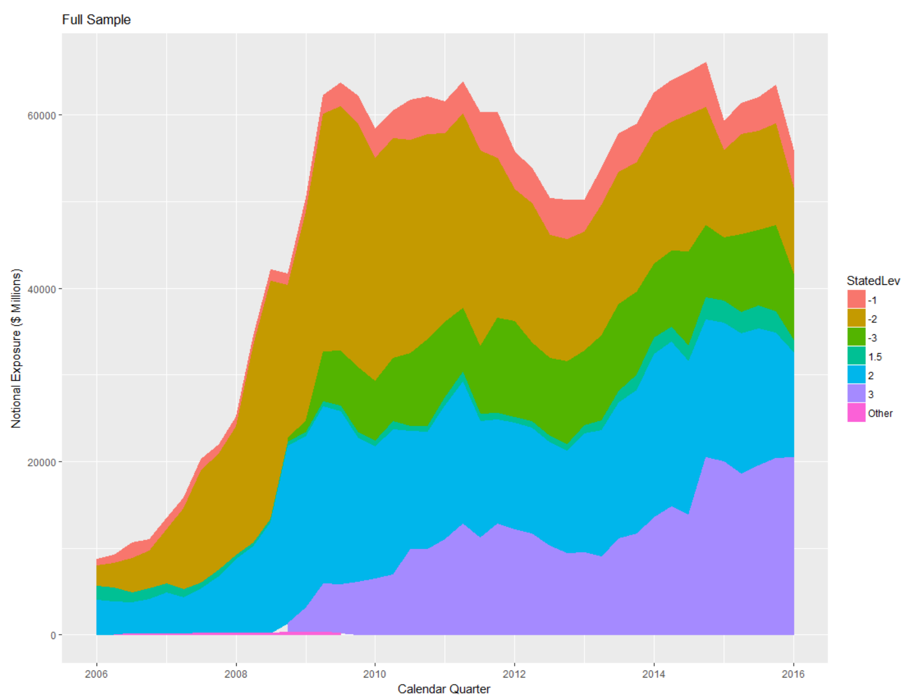
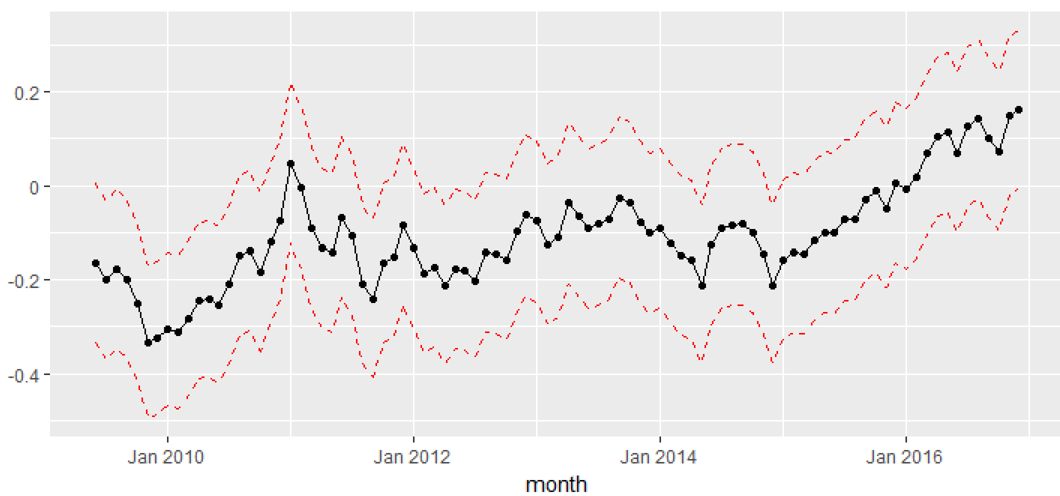


Figure 5: Correlations and Predictive Coefficients in 36-month Moving Windows

Sub-figure (a) presents the moving correlations between the innovations in monthly ψ and the LCT measure from Boguth and Simutin (2018). Sub-figure (b) presents the moving predictive coefficients from regressing the average monthly BAB returns over the next six months on the six-month moving average of LCT. Both the correlations and the regression coefficients are estimated in the same 36-month moving estimation windows. The first 36-month window ends in June 2009 and the last one ends in December 2016. One standard error confidence intervals are indicated with the dashed lines.

(a) Moving Correlations



(b) Moving Predictive Coefficients

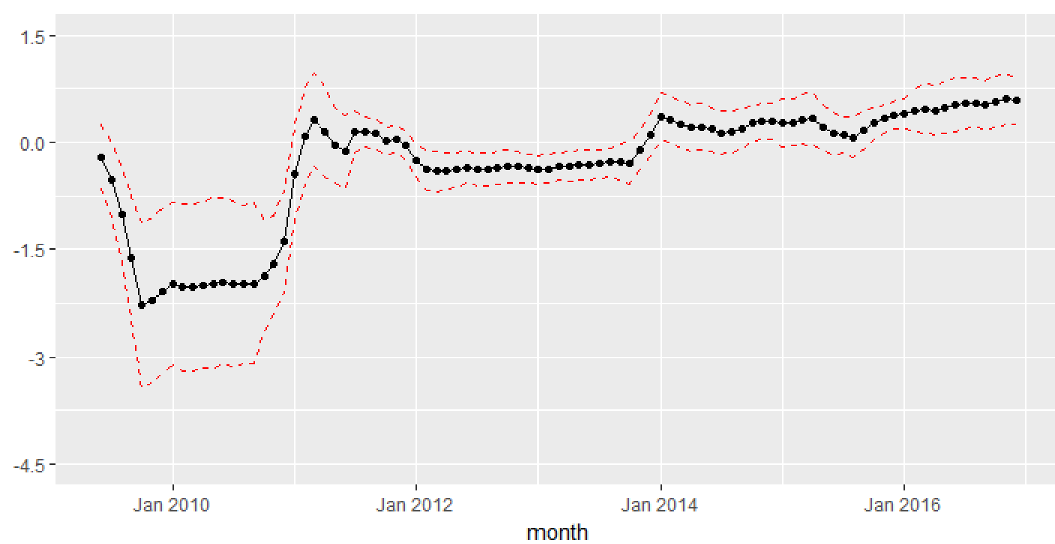


Table 1: Summary Statistics

Panel A presents the summary statistics of the variables used to compute α_{it} in Eq. (1). For funds with the stated leverage multiple indicated in Column δ, Column N reports the number of unique CRSP fund names. $\overline{ExpRatio_{it}} = \sum_{i=1}^{N}\left(\sum_{t=1}^{T_i} ExpRatio_{it}/T_i\right)/N$ is the cross-sectional mean of the time series average of annual expense ratios. $\overline{\sigma_i\left(ExpRatio_{it}\right)} = \sum_{i=1}^{N}\sigma_i\left(ExpRatio_{it}\right)/N$ is the cross-sectional mean of the time series standard deviation of annual expense ratios. $\hat{\delta}_i$ is the OLS regression beta from regressing the daily fund gross returns on the daily benchmark returns. Columns "$\overline{\hat{\delta}_i}$" and "$\sigma\left(\hat{\delta}_i\right)$" report the cross-sectional mean and standard deviation of $\hat{\delta}_i$. $\overline{R_i^2} = \sum_{i=1}^{N}\left(1 - V_i\left(\alpha_{it}\right)/V_i\left(r_{it}\right)\right)/N$ is the cross-sectional mean of the portion of leveraged fund returns that are explained by the underlying returns. $\overline{\sigma_i\left(\alpha_{it}\right)} = \sum_{i=1}^{N}\sigma_i\left(\alpha_{it}\right)/N$ is the cross-sectional mean of the time series standard deviation of α_{it}. α_{it} and $ExpRatio_{it}$ are in annualized percentage points. The sample period starts on June 30, 2006 and ends on December 30, 2016.

Panel A

δ	N	$\overline{ExpRatio_{it}}$	$\overline{\sigma_i\left(ExpRatio_{it}\right)}$	$\overline{\hat{\delta}_i}$	$\sigma\left(\hat{\delta}_i\right)$	$\overline{R_i^2}$	$\overline{\sigma_i\left(\alpha_{it}\right)}$
-1	141	1.53	0.02	-1.00	0.02	99.67	10.60
-2	186	1.32	0.01	-2.00	0.02	99.87	18.67
-3	47	0.94	0.002	-3.01	0.06	99.92	12.57
1.5	61	2.05	0.06	1.50	0.003	99.93	12.58
2	188	1.34	0.02	2.00	0.01	99.92	13.11
3	47	0.95	0.01	3.00	0.03	99.91	13.19
Other	8	1.76	0.02			99.75	42.27
ALL	678	1.52	0.02			99.85	14.42

Panel B reports the summary statistics for our cost of leverage measure (r^c), our spread measure for the shadow cost of leverage constraints (ψ), the one-month Treasury bill rate (T-bill 1M), the general collateral (GC) repo rate, the effective fed funds rate (EFFR), the TED spread (TED), and the EFFR-GC repo spread at the daily and monthly frequencies. Monthly variables are the monthly average of the daily variables. All variables are in annualized percentage points.

Panel B

	N	Mean	SD	Median	Min	Max	Skew	Kurtosis	IQR	Q0.25	Q0.75	AR1 Coef
						Daily						
r^c	2,645	1.28	3.90	0.79	-68.71	56.90	-0.70	61.78	2.48	-0.26	2.22	-0.03
ψ	2,645	0.30	3.59	0.22	-69.57	56.32	-1.54	83.97	2.20	-0.85	1.35	-0.22
ψ^{adj}	2,645	0.51	4.35	0.34	-96.62	76.82	-1.41	141.91	2.50	-0.87	1.63	-0.23
T-Bill 1M	2,645	0.84	1.62	0.09	0	5.27	1.89	1.92	0.24	0.03	0.27	0.99
GC repo	2,645	0.98	1.73	0.16	-0.01	5.31	1.78	1.44	0.27	0.08	0.35	0.99
EFFR	2,645	1.04	1.78	0.16	0.02	5.50	1.71	1.17	0.30	0.10	0.40	0.99
TED	2,645	0.50	0.52	0.32	0.09	4.58	3.11	12.88	0.31	0.21	0.52	0.99
						Monthly						
r^c	126	1.28	1.63	0.63	-1.07	7.11	1.84	2.18	0.55	0.49	1.04	0.87
ψ	126	0.30	0.47	0.42	-1.43	1.94	-0.87	2.89	0.36	0.18	0.54	0.09
ψ^{adj}	126	0.51	0.57	0.46	-1.00	3.55	2.22	8.83	0.35	0.27	0.62	0.35
T-Bill 1M	126	0.84	1.62	0.09	0.00	5.21	1.87	1.83	0.23	0.03	0.26	0.97
GC repo	126	0.98	1.73	0.16	0.02	5.24	1.75	1.37	0.27	0.09	0.36	0.97
EFFR	126	1.04	1.79	0.16	0.05	5.27	1.69	1.11	0.28	0.12	0.40	0.97
TED	126	0.50	0.50	0.31	0.12	3.41	2.72	9.22	0.30	0.21	0.51	0.87

Table 2: Market State and Shadow Cost of Leverage Constraints

This table presents the average of monthly ψ, ψ^{adj}, $\psi - \psi^{\text{adj}}$, the TED spread, and the other proxies for funding conditions upon different market states. Month t is defined as a Low (High) state if the 36-month cumulative return of the market (MKT3Y) and the average VIX for month t is below (above) the respective 10^{th} (90^{th}) percentile within our sample period. Month t is a Mid state if the same variables are between the 10^{th} and 90^{th} percentiles. Data are converted into monthly frequency. For daily variables, we use the monthly averages. For quarterly variables, we use the quarterly value for months in that quarter. We use the AR(1) innovations in monthly LCT and MD to be consistent with ICR and LEV. The sample period includes the 126 months between June 2006 and December 2016. All variables are in the same units as that of the summary statistics displayed in Panel B of the Table 1.

Panel A - MKT

State	ψ	ψ^{adj}	$\psi - \psi^{\text{adj}}$	TED	ICR	LEV	LCT	MD	MKT	VIX
Low	0.07	0.95	-0.88	1.04	-0.25	-24.86	-2.51	-0.06	-2.86	40.10
Mid	0.30	0.38	-0.08	0.45	-0.01	2.43	-2.12	1.88	0.98	18.33
High	0.52	0.50	0.02	0.29	0.06	-2.07	-4.03	0.39	1.53	15.86

Panel B - VIX

State	ψ	ψ^{adj}	$\psi - \psi^{\text{adj}}$	TED	ICR	LEV	LCT	MD	MKT	VIX
Low	0.23	0.38	-0.15	0.38	0.08	5.67	-2.46	3.78	1.41	11.89
Mid	0.33	0.38	-0.05	0.44	0.00	1.02	-2.24	1.88	0.90	18.56
High	0.18	1.06	-0.88	1.05	-0.30	-21.75	-3.11	-3.47	-2.13	42.27

Table 3: Quarter End Regressions

Panel A of this table reports the time-series regression of ψ, ψ^{adj}, $\psi - \psi^{\text{adj}}$, the TED spread, and the GC repo rate on the quarter-end indicator variable QtrEnd, which equals one for the first and last trading days of a quarter. The regression controls for the lagged dependent variable. t-statistics are adjusted following Newey and West (1987) with 22 lags. Panel B reports the average ψ on quarter-end and non-quarter-end days year by year. The regression includes 2,645 daily observations between June 30, 2006 through December 30, 2016. All variables are in annualized percentage points.

Panel A - OLS Regression

	ψ_t	ψ_t^{adj}	$\psi_t - \psi_t^{\text{adj}}$	TED_t	GC_Repo_t
	(1)	(2)	(3)	(4)	(5)
QtrEnd	1.31***	1.36***	0.06	−0.01	0.02*
	(4.49)	(3.99)	(0.25)	(−1.45)	(1.87)
ψ_{t-1}	−0.22***				
	(−5.87)				
ψ_{t-1}^{adj}		−0.23***			
		(−4.59)			
$\psi_{t-1} - \psi_{t-1}^{\text{adj}}$			−0.02		
			(−0.46)		
TED_{t-1}				0.99***	
				(121.72)	
GC_Repo_{t-1}					1.00***
					(616.30)
Constant	0.32***	0.58***	−0.21***	0.004	0.002
	(5.19)	(8.89)	(−4.75)	(1.18)	(1.37)
N	2,645	2,645	2,645	2,645	2,645
R^2	0.05	0.05	0.0004	0.99	0.99
Adjusted R^2	0.05	0.05	−0.0003	0.99	0.99

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Panel B - Year by Year

ψ_t	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
QtrEnd	3.06	5.33	1.21	-0.73	0.38	1.71	1.42	1.44	0.63	0.62	1.20
Non-QtrEnd	-0.18	-0.27	0.03	-0.01	0.33	0.45	0.32	0.51	0.51	0.52	0.46
Diff	3.24	5.60	1.18	-0.72	0.05	1.26	1.10	0.93	0.12	0.10	0.74

Table 4: Predicting BAB Returns with ψ

This table reports the times series predictive regression of the average monthly BAB returns in the next one, six, or 12 months. Panel A uses the one-, six-, and 12-month moving averages of ψ as the predictor, respectively. Panel B uses the one-, six-, and 12-month moving averages of an alternative version of ψ_t, defined as $\psi^{EFFR} \equiv r^c - EFFR$, respectively. Panel C uses the six-month moving averages of ψ and LCT from Boguth and Simutin (2018), the TED spread (TED), and the NYSE margin debt (MD) from Asness, Frazzini, Gormsen, and Pedersen (2016) as the predictors. The sample period is from June 30, 2006 through December 30, 2016, and the first observations of the one-, six-, and 12-month moving averages are available at the end of July 2006, December 2006, and June 2007, respectively. We report Newey-West t-statistics with 12 lags. The monthly BAB returns are in percentage points per month. MD is quoted as percentage points of the total NYSE market capitalization. All the other variables are in percentage points per annum.

Panel A - ψ predicting BAB returns

	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ψ_t	0.89	0.91**	0.86***						
	(0.90)	(2.26)	(3.14)						
$\psi^{MA6}_{t-5,t}$				3.10**	2.77***	2.90***			
				(2.56)	(3.85)	(3.27)			
$\psi^{MA12}_{t-11,t}$							3.52**	3.41***	3.24**
							(2.52)	(2.78)	(2.59)
Constant	0.09	0.11	0.12	−0.57	−0.45	−0.47	−0.73	−0.64	−0.52
	(0.16)	(0.31)	(0.40)	(−0.99)	(−1.08)	(−1.03)	(−1.12)	(−1.08)	(−0.91)
N	126	126	126	121	121	121	115	115	115
R^2	0.02	0.10	0.13	0.07	0.27	0.43	0.08	0.34	0.48
Adjusted R^2	0.01	0.09	0.12	0.07	0.26	0.42	0.07	0.33	0.47

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Panel B - ψ^{EFFR} predicting BAB returns

	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ψ^{EFFR}_t	1.18	1.21**	1.15***						
	(1.19)	(2.59)	(3.29)						
$\psi^{MA6,EFFR}_{t-5,t}$				3.06***	2.97***	2.86***			
				(3.71)	(4.56)	(4.14)			
$\psi^{MA12,EFFR}_{t-11,t}$							3.22***	3.09***	2.74***
							(3.50)	(3.53)	(3.17)
Constant	0.07	0.09	0.10	−0.38	−0.34	−0.29	−0.45	−0.36	−0.21
	(0.15)	(0.28)	(0.36)	(−1.07)	(−1.13)	(−0.94)	(−1.13)	(−0.93)	(−0.55)
N	126	126	126	121	121	121	115	115	115
R^2	0.04	0.20	0.26	0.11	0.47	0.64	0.11	0.47	0.58
Adjusted R^2	0.03	0.19	0.26	0.10	0.47	0.64	0.10	0.46	0.57

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Panel C - Additional Controls

	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\psi^{MA6}_{t-5,t}$	1.70**	1.66***	2.02***	3.01**	2.39***	2.48***	4.80***	3.14***	3.11***
	(2.10)	(3.90)	(3.29)	(2.49)	(3.81)	(2.76)	(3.63)	(5.32)	(3.57)
TED_t	−1.24***	−0.98**	−0.78						
	(−4.44)	(−2.18)	(−1.45)						
$LCT^{MA6}_{t-5,t}$				−1.31	−5.50	−6.17			
				(−0.16)	(−0.63)	(−1.06)			
MD_t							−4.07**	−0.88	−0.49
							(−2.09)	(−1.52)	(−0.91)
Constant	0.46	0.36	0.18	0.83	5.40	6.10	7.62*	1.32	0.52
	(1.24)	(1.52)	(0.54)	(0.10)	(0.60)	(0.99)	(1.98)	(0.96)	(0.42)
N	121	121	121	121	121	121	121	121	121
R^2	0.11	0.36	0.51	0.07	0.28	0.45	0.12	0.28	0.43
Adjusted R^2	0.09	0.35	0.50	0.06	0.27	0.44	0.11	0.27	0.42

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 5: Contemporaneous Correlation with BAB Returns

This table reports on the contemporaneous relationship between BAB returns and our spread measure (ψ) at the daily frequency. Across all specifications, we control for the market excess return (MKT). We additionally control for lagged ψ, changes in TED spread (ΔTED), and changes in VIX (ΔVIX), respectively, in columns (2) through (4), and together in Column (5). We report Newey-West t-statistics with 22 lags. The sample period is between June 30, 2006 and December 30, 2016. The daily BAB and MKT are in percentage points. All the other variables are in percentage points per annum.

	ψ_t	ψ_t	ψ_t	ψ_t	ψ_t
	(1)	(2)	(3)	(4)	(5)
BAB_t	-0.79^{***}	-0.76^{***}	-0.86^{***}	-0.70^{***}	-0.80^{***}
	(-3.21)	(-3.37)	(-3.80)	(-2.89)	(-3.29)
ψ_{t-1}		-0.22^{***}	-0.22^{***}	-0.21^{***}	-0.22^{***}
		(-5.75)	(-5.94)	(-5.44)	(-5.68)
ΔTED_t			-8.06^{***}		-8.10^{***}
			(-4.38)		(-4.32)
ΔVIX_t				0.15	0.15
				(1.04)	(1.20)
MKT_t	-0.22	-0.20	-0.28	-0.002	-0.07
	(-0.99)	(-0.96)	(-1.29)	(-0.005)	(-0.20)
Constant	0.32^{***}	0.39^{***}	0.39^{***}	0.38^{***}	0.38^{***}
	(6.14)	(6.20)	(6.31)	(6.05)	(6.19)
N	2,645	2,644	2,644	2,644	2,644
R^2	0.02	0.07	0.09	0.07	0.09
Adjusted R^2	0.02	0.07	0.08	0.07	0.09

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 6: Predicting BAB Returns with LCT

This table reports the times series predictive regression of the average monthly BAB returns in the next one, six, or 12 months using the one-, six-, or 12-month moving average of leverage constraint tightness (LCT) from Boguth and Simutin (2018). LCT is downloaded from the authors' websites starting from January 1980 though December 2014 and supplemented by our replicated LCT to extend to December 2016. Panel A uses LCT between January 1980 and December 2016. Panels B and C examine the predictive power of LCT between July 2006 through December 2016. In Panel C, specifications (1) through (3) include the 12-month moving average LCT (LCT^{MA12}), CoMove (defined as the correlation between innovations in LCT and monthly ψ in the same past 12 months), and their interaction term; specifications (4) through (6) include LCT^{MA12}, DemandShift (an indicator equal to one if CoMove is positive), and their interaction term. LCT^{MA12} and CoMove are estimated in the same 12-month window for each month. To facilitate interpretations, LCT^{MA12} and CoMove are de-meaned. We report Newey and West (1987) t-statistics with 12 lags. The monthly BAB returns are in percentage points.

Panel A - January 1980 to December 2016

	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LCT_t	1.39	1.56	1.89**						
	(1.07)	(1.63)	(2.26)						
$LCT^{MA6}_{t-5,t}$				4.74*	5.81**	7.15***			
				(1.72)	(2.47)	(3.56)			
$LCT^{MA12}_{t-11,t}$							7.91***	9.66***	10.30***
							(2.60)	(3.45)	(3.98)
Constant	−0.59	−0.75	−1.11	−4.17	−5.32**	−6.75***	−7.56**	−9.45***	−10.14***
	(−0.38)	(−0.64)	(−1.11)	(−1.34)	(−2.01)	(−3.01)	(−2.23)	(−3.04)	(−3.56)
N	444	444	444	439	439	439	433	433	433
R^2	0.002	0.01	0.02	0.01	0.04	0.09	0.01	0.08	0.13
Adjusted R^2	−0.001	0.01	0.02	0.004	0.04	0.09	0.01	0.07	0.13

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Panel B - July 2006 to December 2016

	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LCT_t	1.76	−2.10	−2.98**						
	(0.63)	(−0.97)	(−2.15)						
$LCT^{MA6}_{t-5,t}$				−13.58	−15.24*	−16.26**			
				(−1.51)	(−1.76)	(−2.55)			
$LCT^{MA12}_{t-11,t}$							−28.62**	−28.15**	−24.76**
							(−2.29)	(−2.10)	(−2.22)
Constant	−1.49	2.59	3.51***	14.52	16.28*	17.38***	30.20**	29.77**	26.29**
	(−0.47)	(1.21)	(2.66)	(1.57)	(1.84)	(2.68)	(2.32)	(2.15)	(2.28)
N	126	126	126	121	121	121	115	115	115
R^2	0.002	0.01	0.04	0.02	0.14	0.23	0.06	0.25	0.31
Adjusted R^2	−0.01	0.004	0.03	0.02	0.13	0.22	0.05	0.25	0.30

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Panel C - LCT interacted with CoMove and DemandShift (July 2006 to December 2016)

	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$	BAB_{t+1}	$BAB^{MA6}_{t+1,t+6}$	$BAB^{MA12}_{t+1,t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)
$LCT^{MA12}_{t-11,t}$	−0.36***	−0.34***	−0.28***	−0.46***	−0.59***	−0.50***
	(−3.12)	(−5.00)	(−4.38)	(−2.83)	(−4.01)	(−4.97)
$CoMove_t$	0.73	1.54***	1.46***			
	(0.71)	(4.02)	(3.39)			
$LCT^{MA12}_{t-11,t} * CoMove_t$	0.92***	1.15***	0.91***			
	(6.44)	(6.68)	(5.75)			
$DemandShift_t$				0.65*	0.21	0.07
				(1.69)	(0.95)	(0.42)
$LCT^{MA12}_{t-11,t} * DemandShift_t$				0.38*	0.55***	0.44***
				(1.97)	(3.27)	(4.62)
Constant	0.67***	0.81***	0.79***	0.29	0.60***	0.66***
	(3.20)	(7.39)	(6.67)	(0.96)	(3.39)	(3.63)
N	115	115	115	115	115	115
R^2	0.11	0.62	0.69	0.09	0.45	0.50
Adjusted R^2	0.08	0.61	0.68	0.06	0.44	0.49

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 7: Univariate Quintile Sort on β^{ψ}

This table reports univariate portfolio analysis of the relation between $\beta^{\psi}$and future stock returns. Each month t, all stocks in the sample are sorted into quintile portfolios based on ascending order of β^{ψ}. The columns labeled "1" through "5" present results for the first through fifth β^{ψ} quintile portfolios. The column labeled "High-Low" presents results for the zero-investment portfolio that is long stocks in the fifth quintile portfolio and short the first quintile portfolio. This table shows the average month $t+1$ value-weighted excess returns for these portfolios and alphas relative to the CAPM, CAPM+BAB, FF3, FFC, Q, and FF5 factor models. The factor sensitivities are reported relative to the FF5 factor model. Newey and West (1987) t-statistics with 12 lags are reported in parentheses. The row labeled "Pre-Formation" shows the time-series average of the value-weighted average of pre-formation β^{ψ} for each of the portfolios. The row labeled "Post-Formation" presents the corresponding post-formation β^{ψ}, calculated as the slope coefficient on $\Delta\psi$ from a regression of the post-formation daily portfolio excess returns on the contemporaneous market excess return and $\Delta\psi$. The t-statistics reported in parentheses for the post-formation sensitivities are adjusted following Newey and West (1987) with 22 lags. The first portfolio is formed at the end of June 2007, and the last portfolio at the end of December 2016, covering 115 months.

Panel A - Full Sample

Model	Value	1	2	3	4	5	High-Low
Excess Return	$ExcessReturn$	1.02	0.82	0.69	0.61	0.27	-0.75
		(2.0)	(1.8)	(1.5)	(1.2)	(0.4)	(-2.3)
CAPM	α	0.31	0.23	0.11	-0.06	-0.58	-0.88
		(1.9)	(2.8)	(2.1)	(-1.0)	(-2.7)	(-3.0)
CAPM+BAB	α	0.29	0.19	0.10	0.01	-0.47	-0.76
		(1.9)	(1.9)	(1.7)	(0.1)	(-2.1)	(-2.3)
FF3	α	0.26	0.20	0.12	-0.02	-0.52	-0.78
		(2.1)	(2.2)	(2.0)	(-0.3)	(-2.5)	(-2.9)
FFC	α	0.26	0.18	0.11	-0.01	-0.49	-0.74
		(2.0)	(2.3)	(2.1)	(-0.1)	(-2.6)	(-2.8)
Q	α	0.38	0.21	0.14	0.05	-0.39	-0.75
		(2.3)	(2.3)	(2.3)	(0.8)	(-1.9)	(-2.3)
FF5	α	0.28	0.15	0.13	-0.02	-0.39	-0.67
		(2.4)	(1.3)	(2.0)	(-0.3)	(-1.7)	(-2.3)
	β^{MKT}	1.11	0.97	0.90	1.04	1.17	0.06
		(27.4)	(28.8)	(52.7)	(38.4)	(40.8)	(1.1)
	β^{SMB}	0.20	-0.01	-0.03	-0.12	0.20	0.00
		(2.9)	(-0.4)	(-1.3)	(-1.7)	(2.4)	(-0.0)
	β^{HML}	-0.27	-0.17	0.03	0.14	0.37	0.64
		(-2.2)	(-2.1)	(0.7)	(2.6)	(2.0)	(2.1)
	β^{RMW}	-0.12	0.07	-0.02	0.01	-0.13	-0.01
		(-0.9)	(1.0)	(-0.3)	(0.1)	(-0.8)	(-0.0)
	β^{CMA}	0.17	0.20	-0.02	-0.15	-0.60	-0.77
		(0.9)	(1.8)	(-0.3)	(-1.8)	(-2.8)	(-2.3)
Pre-Formation	β^{ψ}	-14.63	-5.22	0.11	5.89	16.34	30.97
Post-Formation	β^{ψ}	-1.07	-0.87	-0.67	1.16	3.63	4.70
		(-2.8)	(-2.4)	(-3.2)	(4.1)	(2.3)	(2.5)
	N-Stocks	724	724	724	724	724	
	N-Months	115	115	115	115	115	115

Panel B - Liquid Sample ($\leq$ NYSE 80^{th} percentile Amihud's ILLIQ)

Model	Value	1	2	3	4	5	High-Low
Excess Return	$ExcessReturn$	1.04	0.75	0.73	0.64	0.27	-0.76
		(2.1)	(1.6)	(1.7)	(1.2)	(0.4)	(-2.5)
CAPM	α	0.36	0.17	0.17	-0.02	-0.54	-0.90
		(2.7)	(1.8)	(2.6)	(-0.4)	(-3.1)	(-3.5)
CAPM+BAB	α	0.34	0.13	0.16	0.04	-0.45	-0.79
		(2.6)	(1.2)	(2.2)	(0.4)	(-2.4)	(-2.7)
FF3	α	0.32	0.14	0.17	0.01	-0.48	-0.80
		(2.7)	(1.4)	(2.5)	(0.1)	(-2.7)	(-3.2)
FFC	α	0.31	0.12	0.16	0.03	-0.45	-0.75
		(2.6)	(1.4)	(2.4)	(0.4)	(-2.8)	(-3.1)
Q	α	0.40	0.16	0.19	0.07	-0.36	-0.76
		(3.0)	(1.5)	(3.2)	(1.2)	(-2.1)	(-2.5)
FF5	α	0.31	0.09	0.17	-0.01	-0.35	-0.66
		(2.3)	(0.8)	(2.2)	(-0.1)	(-1.7)	(-2.2)
	β^{MKT}	1.07	0.97	0.88	1.05	1.14	0.06
		(33.0)	(28.0)	(58.0)	(35.3)	(35.4)	(1.1)
	β^{SMB}	0.12	-0.02	-0.04	-0.17	0.11	-0.01
		(1.9)	(-0.4)	(-1.6)	(-2.8)	(1.3)	(-0.1)
	β^{HML}	-0.26	-0.15	0.00	0.12	0.43	0.69
		(-2.4)	(-2.1)	(-0.1)	(2.6)	(2.4)	(2.4)
	β^{RMW}	-0.07	0.08	-0.02	0.04	-0.10	-0.03
		(-0.5)	(1.1)	(-0.4)	(0.6)	(-0.5)	(-0.1)
	β^{CMA}	0.22	0.11	0.04	-0.08	-0.66	-0.88
		(1.3)	(1.1)	(0.7)	(-0.8)	(-3.7)	(-2.7)
Pre-Formation	β^{ψ}	-13.03	-4.77	-0.14	4.82	13.91	26.95
Post-Formation	β^{ψ}	-1.28	-1.12	-0.63	0.91	3.51	4.79
		(-3.8)	(-3.5)	(-2.9)	(3.1)	(2.3)	(2.7)
	N-Stocks	398	398	398	398	398	
	N-Months	115	115	115	115	115	115

Panel C - Large Cap Sample ($\geq$ NYSE 50^{th} percentile MKTCAP)

Model	Value	1	2	3	4	5	High-Low
Excess Return	$ExcessReturn$	0.93	0.75	0.74	0.58	0.33	-0.60
		(1.8)	(1.7)	(1.8)	(1.2)	(0.5)	(-2.0)
CAPM	α	0.29	0.20	0.20	-0.06	-0.45	-0.74
		(2.6)	(2.2)	(2.5)	(-0.8)	(-2.7)	(-3.0)
CAPM+BAB	α	0.24	0.16	0.19	0.00	-0.37	-0.62
		(1.9)	(1.6)	(2.0)	(-0.1)	(-1.9)	(-2.1)
FF3	α	0.24	0.17	0.19	-0.03	-0.39	-0.63
		(2.1)	(1.9)	(2.3)	(-0.3)	(-2.4)	(-2.6)
FFC	α	0.22	0.16	0.19	-0.01	-0.36	-0.58
		(2.2)	(1.7)	(2.3)	(-0.2)	(-2.4)	(-2.6)
Q	α	0.30	0.18	0.23	0.02	-0.31	-0.60
		(2.5)	(1.7)	(3.5)	(0.3)	(-1.9)	(-2.0)
FF5	α	0.22	0.12	0.20	-0.08	-0.25	-0.47
		(1.5)	(1.1)	(2.3)	(-0.8)	(-1.4)	(-1.6)
	β^{MKT}	1.06	0.93	0.86	1.04	1.12	0.07
		(34.4)	(33.2)	(39.7)	(35.2)	(36.5)	(1.3)
	β^{SMB}	0.03	-0.08	-0.07	-0.18	-0.07	-0.09
		(0.4)	(-2.2)	(-2.0)	(-4.5)	(-0.6)	(-0.7)
	β^{HML}	-0.25	-0.12	-0.05	0.12	0.41	0.66
		(-2.5)	(-2.3)	(-1.1)	(2.4)	(2.3)	(2.5)
	β^{RMW}	-0.03	0.12	-0.04	0.12	-0.18	-0.15
		(-0.2)	(1.5)	(-1.0)	(2.0)	(-0.9)	(-0.5)
	β^{CMA}	0.22	0.10	0.07	-0.07	-0.53	-0.75
		(1.3)	(0.9)	(1.0)	(-0.8)	(-2.7)	(-2.2)
Pre-Formation	β^{ψ}	-11.23	-4.05	-0.14	4.06	12.05	23.28
Post-Formation	β^{ψ}	-1.51	-1.26	-0.72	0.85	3.40	4.91
		(-5.2)	(-3.4)	(-2.4)	(3.1)	(2.3)	(2.9)
	N-Stocks	179	179	179	179	179	
	N-Months	115	115	115	115	115	115

Table 8: Univariate Sort on $\beta^{\mathbf{TED}}$

This table reports univariate portfolio analysis of the relation between β^{TED} and future stock returns. Each month t, all stocks in the sample are sorted into quintile portfolios based on ascending order of β^{TED}. The columns labeled "1" through "5" present results for the first through fifth β^{TED} quintile portfolios. The column labeled "High-Low" presents results for the zero-investment portfolio that is long stocks in the fifth quintile portfolio and short the first quintile portfolio. This table shows the average month $t+1$ value-weighted excess returns for these portfolios and alphas relative to the CAPM, CAPM+BAB, FF3, FFC, Q, and FF5 factor models. The factor sensitivities are reported relative to the FF5 factor model. Newey and West (1987) t-statistics with 12 lags are reported in parentheses. The row labeled "Pre-Formation" shows the time-series average of the value-weighted average of pre-formation β^{TED} for each of the portfolios. The row labeled "Post-Formation" presents the corresponding post-formation β^{TED}, calculated as the slope coefficient on ΔTED from a regression of the post-formation daily portfolio excess returns on the contemporaneous market excess return and ΔTED. The t-statistics reported in parentheses for the post-formation sensitivities are adjusted following Newey and West (1987) with 22 lags. The first portfolio is formed at the end of June 2007, and the last portfolio at the end of December 2016, covering 115 months.

Panel A - Full Sample

Model	Value	1	2	3	4	5	High-Low
Excess Return	$ExcessReturn$	0.70	0.60	0.60	0.79	0.53	-0.17
		(1.0)	(1.1)	(1.4)	(1.6)	(0.8)	(-0.6)
CAPM	α	-0.13	-0.03	0.03	0.18	-0.24	-0.10
		(-0.8)	(-0.3)	(0.4)	(1.8)	(-1.4)	(-0.4)
CAPM+BAB	α	-0.25	-0.09	0.01	0.19	-0.09	0.16
		(-1.4)	(-1.0)	(0.2)	(1.7)	(-0.4)	(0.5)
FF3	α	-0.21	-0.07	0.01	0.18	-0.13	0.08
		(-1.1)	(-0.7)	(0.2)	(1.9)	(-0.9)	(0.3)
FFC	α	-0.22	-0.07	0.00	0.18	-0.10	0.12
		(-1.1)	(-0.7)	(0.0)	(1.9)	(-0.8)	(0.5)
Q	α	-0.08	0.01	0.03	0.23	0.03	-0.17
		(-0.5)	(0.1)	(0.4)	(2.4)	(0.2)	(-0.6)
FF5	α	-0.15	-0.06	-0.04	0.14	-0.02	0.14
		(-0.7)	(-0.6)	(-0.5)	(1.6)	(-0.1)	(0.4)
	β^{MKT}	1.30	1.02	0.95	0.97	1.02	-0.28
		(18.8)	(25.0)	(88.3)	(36.0)	(19.3)	(-2.5)
	β^{SMB}	0.29	-0.02	-0.08	0.03	0.12	-0.17
		(2.6)	(-0.4)	(-3.9)	(0.6)	(1.5)	(-1.0)
	β^{HML}	-0.14	-0.09	-0.13	-0.07	0.38	0.52
		(-1.0)	(-1.1)	(-3.9)	(-1.5)	(2.1)	(1.7)
	β^{RMW}	0.10	0.08	0.04	0.02	-0.36	-0.46
		(0.5)	(0.8)	(0.7)	(0.3)	(-1.8)	(-1.3)
	β^{CMA}	-0.36	-0.11	0.21	0.19	-0.08	0.28
		(-2.9)	(-1.6)	(3.5)	(3.6)	(-0.4)	(1.0)
Pre-Formation	β^{ψ}	-1875.62	-667.39	-31.23	590.38	1728.38	3604.00
Post-Formation	β^{ψ}	-0.04	-0.01	0.09	-0.08	-0.01	0.17
		(-1.3)	(-0.8)	(1.5)	(-1.7)	(-0.6)	(1.7)
	N-Stocks	724	724	724	724	724	
	N-Months	115	115	115	115	115	115

Panel B - Liquid Sample ($\leq 80^{th}$ percentile NYSE Amihud's $Illq_t$):

Model	Value	1	2	3	4	5	High-Low
Excess Return	$ExcessReturn$	0.74	0.62	0.61	0.76	0.59	-0.15
		(1.1)	(1.2)	(1.4)	(1.5)	(0.9)	(-0.5)
CAPM	α	-0.03	0.01	0.04	0.16	-0.17	-0.14
		(-0.2)	(0.2)	(0.5)	(1.4)	(-1.1)	(-0.5)
CAPM+BAB	α	-0.12	-0.03	0.03	0.17	-0.03	0.08
		(-0.7)	(-0.4)	(0.4)	(1.4)	(-0.2)	(0.3)
FF3	α	-0.11	-0.01	0.03	0.16	-0.06	0.05
		(-0.7)	(-0.1)	(0.3)	(1.4)	(-0.4)	(0.2)
FFC	α	-0.11	-0.01	0.02	0.16	-0.03	0.09
		(-0.7)	(-0.2)	(0.2)	(1.5)	(-0.2)	(0.3)
Q	α	0.02	0.02	0.05	0.21	0.06	-0.15
		(0.2)	(0.3)	(0.5)	(1.8)	(0.3)	(-0.5)
FF5	α	-0.08	0.01	-0.04	0.14	0.03	0.11
		(-0.5)	(0.1)	(-0.4)	(1.3)	(0.2)	(0.4)
	β^{MKT}	1.24	0.98	0.96	0.95	1.04	-0.20
		(20.9)	(54.0)	(56.8)	(29.7)	(19.7)	(-1.9)
	β^{SMB}	0.20	-0.07	-0.07	-0.01	0.03	-0.18
		(2.1)	(-1.7)	(-2.3)	(-0.1)	(0.3)	(-1.0)
	β^{HML}	-0.21	-0.04	-0.14	-0.03	0.46	0.66
		(-1.4)	(-0.8)	(-3.4)	(-0.6)	(2.2)	(2.0)
	β^{RMW}	0.12	0.02	0.08	-0.02	-0.26	-0.38
		(0.8)	(0.3)	(1.4)	(-0.2)	(-1.4)	(-1.2)
	β^{CMA}	-0.33	-0.06	0.22	0.14	-0.11	0.22
		(-2.9)	(-0.9)	(2.5)	(2.3)	(-0.5)	(0.7)
Pre-Formation	β^{ψ}	-1556.14	-545.46	6.71	541.92	1538.26	3094.39
Post-Formation	β^{ψ}	-0.02	0.00	-0.07	0.08	-0.02	0.15
		(-1.1)	(0.3)	(-1.5)	(1.3)	(-1.1)	(1.4)
	N-Stocks	398	398	398	398	398	
	N-Months	115	115	115	115	115	115

Panel C - Large Cap Sample ($\geq 50^{th}$ percentile NYSE $MKTCAP_t$):

Model	Value	1	2	3	4	5	High-Low
Excess Return	$ExcessReturn$	0.70	0.54	0.64	0.74	0.58	-0.12
		(1.1)	(1.2)	(1.4)	(1.7)	(0.9)	(-0.4)
CAPM	α	-0.01	-0.03	0.08	0.17	-0.16	-0.15
		(-0.1)	(-0.4)	(0.8)	(1.9)	(-1.1)	(-0.6)
CAPM+BAB	α	-0.11	-0.08	0.06	0.18	-0.05	0.06
		(-0.9)	(-0.8)	(0.6)	(2.0)	(-0.3)	(0.2)
FF3	α	-0.09	-0.06	0.06	0.17	-0.06	0.03
		(-0.6)	(-0.8)	(0.7)	(1.8)	(-0.4)	(0.1)
FFC	α	-0.09	-0.07	0.05	0.17	-0.03	0.05
		(-0.6)	(-0.8)	(0.7)	(1.7)	(-0.2)	(0.2)
Q	α	0.04	-0.04	0.09	0.20	0.01	-0.12
		(0.3)	(-0.6)	(0.8)	(1.9)	(0.1)	(-0.4)
FF5	α	-0.07	-0.06	0.00	0.14	0.02	0.10
		(-0.4)	(-0.8)	(-0.0)	(1.3)	(0.1)	(0.3)
	β^{MKT}	1.18	0.96	0.95	0.92	1.05	-0.13
		(23.1)	(36.7)	(41.5)	(25.4)	(20.0)	(-1.4)
	β^{SMB}	0.07	-0.15	-0.10	-0.05	-0.08	-0.15
		(0.7)	(-3.3)	(-3.6)	(-1.1)	(-1.2)	(-1.0)
	β^{HML}	-0.17	-0.09	-0.12	-0.06	0.45	0.61
		(-1.0)	(-1.7)	(-3.3)	(-0.9)	(2.4)	(1.8)
	β^{RMW}	0.16	0.02	0.08	0.02	-0.21	-0.38
		(1.1)	(0.2)	(1.6)	(0.2)	(-1.3)	(-1.4)
	β^{CMA}	-0.30	0.01	0.20	0.15	-0.12	0.18
		(-2.4)	(0.1)	(3.0)	(1.9)	(-0.6)	(0.6)
Pre-Formation	β^{ψ}	-1271.91	-420.64	39.54	483.22	1344.35	2616.26
Post-Formation	β^{ψ}	-0.04	0.00	0.08	-0.03	-0.01	0.12
		(-1.2)	(0.3)	(1.3)	(-1.4)	(-0.7)	(1.4)
	N-Stocks	179	179	179	179	179	
	N-Months	115	115	115	115	115	115

Table 9: Quintile Portfolio Characteristics

This table presents the equal-weight average characteristics of the univariate quintile portfolios sorted on β^{ψ}. The characteristics include betas with respect to market excess returns (MKT), and other proxies for funding conditions including the VIX index, TED spread, LCT, intermediary capital risk factor (ICR), and leverage factor (LEV). The last column reports idiosyncratic volatility (IVOL). See Data Appendix for the description of these variables. This table reports the times-series average of the monthly estimates. To facilitate readability, we multiply β^{VIX}, β^{TED}, β^{ICR} , $\beta^{\text{LEV}}$and IVOL by 100. The sample period is June 2007 to December 2016.

Panel A - Full Sample

Quintile	β^{ψ}	β^{MKT}	β^{VIX}	β^{TED}	β^{LCT}	β^{ICR}	β^{LEV}	$IVOL$
1	-0.20	1.05	0.03	-0.90	-6.13	4.26	-0.78	0.16
2	-0.05	0.98	0.03	-0.46	-4.31	0.90	-0.38	0.06
3	0.002	0.97	0.05	-0.21	-3.86	-0.42	-0.09	0.06
4	0.06	1.02	0.06	-0.37	-3.59	-0.39	-0.65	0.07
5	0.22	1.14	0.11	-0.94	-5.58	1.25	-0.60	0.15

Panel B - Liquid Sample ($\leq$ NYSE 80^{th} percentile Amihud's ILLIQ)

Quintile	β^{ψ}	β^{MKT}	β^{VIX}	β^{TED}	β^{LCT}	β^{ICR}	β^{LEV}	$IVOL$
1	-0.16	1.10	0.02	-0.28	-6.12	2.47	0.44	0.09
2	-0.05	1.03	0.03	-0.03	-3.83	-0.39	0.45	0.04
3	-0.001	1.03	0.04	0.22	-3.48	-1.54	0.55	0.04
4	0.05	1.07	0.05	-0.05	-3.11	-1.49	-0.11	0.04
5	0.17	1.19	0.09	-0.66	-4.25	-0.27	0.43	0.09

Panel C - Large Cap Sample ($\geq$ NYSE 50^{th} percentile MKTCAP)

Quintile	β^{ψ}	β^{MKT}	β^{VIX}	β^{TED}	β^{LCT}	β^{ICR}	β^{LEV}	$IVOL$
1	-0.12	1.17	-0.004	0.35	-8.28	1.08	1.93	0.04
2	-0.04	1.06	0.005	0.46	-3.53	-1.69	1.60	0.02
3	-0.001	1.06	0.01	0.50	-2.35	-2.65	1.88	0.02
4	0.04	1.10	0.03	0.21	-2.31	-2.50	1.29	0.02
5	0.13	1.25	0.05	0.04	-3.25	-0.98	2.16	0.04

Table 10: Bivariate Portfolio Analysis

This table reports bivariate portfolio analysis sorting first on a control variable and then on β^{ψ}. The control variables include β^{VIX}, β^{TED}, β^{LCT}, β^{LEV}, β^{ICR}, and IVOL. Each month t, all stocks are first sorted into quintile groups based on the control variable in ascending order, and within each control quintile group, the stocks are further sorted into quintile groups in ascending order based on β^{ψ}. The value-weighted excess return for each of the 25 resulting portfolios are calculated. Within each β^{ψ} quintile, we compute the equal-weighted average of the portfolio excess returns across the quintiles of the control variable, which we then refer to as the bivariate β^{ψ} quintile portfolios. The bivariate β^{ψ} $5-1$ portfolio is a zero-investment portfolio that is long the bivariate β^{ψ} quintile 5 portfolio and short the bivariate β^{ψ} quintile 1 portfolio. The table presents the month $t+1$ average excess returns for these bivariate β^{ψ} portfolios, along with the alphas relative to the CAPM, CAPM+BAB, FF3, FFC, Q, and FF5 factor models. The factor sensitivities are reported relative to the FF5 factor model. Newey and West (1987) t-statistics with 12 lags are reported in parentheses. The first portfolio is formed at the end of June, 2007, and the last portfolio at the end of December 2016, covering 115 months.

Panel A - Full Sample

Quintile	Model	Value	β^{TED}	β^{VIX}	β^{LCT}	β^{LEV}	β^{ICR}	$IVOL$
β^{ψ} 1	Excess Return	$ExcessReturn$	0.92	1.00	1.04	1.02	1.15	1.03
β^{ψ} 2			0.81	0.78	0.83	0.83	0.77	0.75
β^{ψ} 3			0.69	0.73	0.63	0.71	0.81	0.62
β^{ψ} 4			0.58	0.68	0.67	0.52	0.53	0.60
β^{ψ} 5			0.34	0.32	0.34	0.29	0.54	0.32
β^{ψ} $5-\beta^{\psi}$ 1	Excess Return	$ExcessReturn$	-0.58	-0.68	-0.70	-0.73	-0.60	-0.71
			(-2.4)	(-2.9)	(-2.7)	(-2.6)	(-3.4)	(-3.0)
	CAPM	α	-0.66	-0.75	-0.82	-0.85	-0.62	-0.77
			(-3.2)	(-3.6)	(-3.7)	(-3.4)	(-3.6)	(-3.5)
	CAPM+BAB	α	-0.59	-0.67	-0.73	-0.76	-0.64	-0.74
			(-2.5)	(-2.7)	(-2.9)	(-2.8)	(-3.7)	(-3.4)
	FF3	α	-0.59	-0.67	-0.73	-0.78	-0.62	-0.70
			(-3.1)	(-3.3)	(-4.1)	(-3.2)	(-3.8)	(-3.5)
	FFC	α	-0.55	-0.64	-0.71	-0.75	-0.63	-0.70
			(-3.3)	(-3.4)	(-4.1)	(-3.3)	(-3.9)	(-3.6)
	Q	α	-0.58	-0.68	-0.70	-0.73	-0.60	-0.71
			(-2.4)	(-2.9)	(-2.7)	(-2.6)	(-3.4)	(-3.0)
	FF5	α	-0.51	-0.55	-0.61	-0.68	-0.57	-0.56
			(-2.4)	(-2.6)	(-3.1)	(-2.6)	(-3.3)	(-2.5)
		β^{MKT}	0.03	0.00	0.07	0.06	0.01	0.04
			(0.6)	(0.0)	(1.6)	(0.9)	(0.2)	(0.7)
		β^{SMB}	-0.03	-0.07	-0.10	0.06	-0.02	-0.29
			(-0.3)	(-0.6)	(-0.8)	(0.5)	(-0.1)	(-1.6)
		β^{HML}	0.41	0.43	0.51	0.40	0.10	0.36
			(2.1)	(1.8)	(2.4)	(1.7)	(1.1)	(1.8)
		β^{RMW}	-0.10	-0.22	-0.13	-0.11	-0.03	-0.31
			(-0.5)	(-0.8)	(-0.6)	(-0.5)	(-0.2)	(-0.9)
		β^{CMA}	-0.38	-0.35	-0.51	-0.41	-0.24	-0.22
			(-1.3)	(-1.5)	(-2.1)	(-1.6)	(-1.5)	(-0.9)

Panel B - Liquid Sample ($\leq$ NYSE 80^{th} percentile Amihud's ILLIQ)

Quintile	Model	Value	β^{TED}	β^{VIX}	β^{LCT}	β^{LEV}	β^{ICR}	$IVOL$
β^{ψ} 1	Excess Return	$ExcessReturn$	0.94	1.06	0.96	1.00	1.02	1.15
β^{ψ} 2			0.84	0.81	0.87	0.87	0.87	0.68
β^{ψ} 3			0.68	0.69	0.68	0.73	0.77	0.72
β^{ψ} 4			0.68	0.58	0.63	0.56	0.68	0.56
β^{ψ} 5			0.36	0.49	0.47	0.32	0.49	0.36
β^{ψ} 5 $-$ β^{ψ} 1	Excess Return	$ExcessReturn$	-0.58	-0.57	-0.48	-0.68	-0.53	-0.79
			(-2.3)	(-2.5)	(-2.2)	(-2.6)	(-2.9)	(-3.3)
	CAPM	α	-0.71	-0.64	-0.61	-0.78	-0.57	-0.86
			(-3.3)	(-3.2)	(-3.2)	(-3.5)	(-3.2)	(-3.8)
	CAPM+BAB	α	-0.64	-0.53	-0.50	-0.68	-0.56	-0.80
			(-2.7)	(-2.4)	(-2.1)	(-2.7)	(-3.3)	(-3.5)
	FF3	α	-0.64	-0.55	-0.52	-0.70	-0.55	-0.77
			(-3.4)	(-2.7)	(-3.0)	(-3.1)	(-3.3)	(-3.8)
	FFC	α	-0.60	-0.52	-0.48	-0.66	-0.55	-0.76
			(-3.1)	(-3.0)	(-2.8)	(-3.2)	(-3.2)	(-3.9)
	Q	α	-0.58	-0.57	-0.48	-0.68	-0.53	-0.79
			(-2.3)	(-2.5)	(-2.2)	(-2.6)	(-2.9)	(-3.3)
	FF5	α	-0.55	-0.49	-0.40	-0.60	-0.55	-0.63
			(-2.7)	(-2.1)	(-2.0)	(-2.3)	(-2.9)	(-2.6)
		β^{MKT}	0.10	0.03	0.08	0.05	0.03	0.01
			(1.7)	(0.6)	(1.4)	(0.8)	(0.7)	(0.1)
		β^{SMB}	-0.06	-0.14	-0.09	-0.02	0.05	-0.23
			(-0.5)	(-1.0)	(-0.8)	(-0.1)	(0.4)	(-1.4)
		β^{HML}	0.42	0.42	0.52	0.48	0.16	0.48
			(2.2)	(1.9)	(2.4)	(2.2)	(2.5)	(2.0)
		β^{RMW}	-0.06	-0.07	-0.10	-0.09	0.11	-0.26
			(-0.3)	(-0.3)	(-0.5)	(-0.4)	(0.9)	(-0.8)
		β^{CMA}	-0.50	-0.35	-0.58	-0.50	-0.27	-0.32
			(-1.8)	(-1.5)	(-2.2)	(-1.7)	(-1.5)	(-1.1)

Panel C - Large Cap Sample ($\geq$ NYSE 50^{th} percentile MKTCAP)

Quintile	Model	Value	β^{TED}	β^{VIX}	β^{LCT}	β^{LEV}	β^{ICR}	$IVOL$
β^{ψ} 1	Excess Return	$ExcessReturn$	0.85	0.91	0.95	0.93	0.92	0.98
β^{ψ} 2			0.83	0.84	0.85	0.85	0.88	0.72
β^{ψ} 3			0.71	0.59	0.75	0.70	0.68	0.75
β^{ψ} 4			0.58	0.69	0.53	0.58	0.67	0.56
β^{ψ} 5			0.38	0.47	0.53	0.35	0.48	0.34
$\beta^{\psi}\,5-\beta^{\psi}\,1$	Excess Return	$ExcessReturn$	-0.47	-0.45	-0.42	-0.58	-0.44	-0.64
			(-1.8)	(-1.9)	(-2.0)	(-2.4)	(-2.0)	(-2.5)
	CAPM	α	-0.59	-0.55	-0.55	-0.71	-0.49	-0.74
			(-2.8)	(-2.8)	(-3.4)	(-3.6)	(-2.5)	(-3.2)
	CAPM+BAB	α	-0.51	-0.44	-0.44	-0.59	-0.45	-0.65
			(-2.2)	(-2.0)	(-2.0)	(-2.5)	(-2.5)	(-2.4)
	FF3	α	-0.52	-0.46	-0.46	-0.62	-0.46	-0.65
			(-2.6)	(-2.3)	(-2.8)	(-3.0)	(-2.4)	(-3.0)
	FFC	α	-0.47	-0.42	-0.42	-0.57	-0.44	-0.61
			(-2.9)	(-2.5)	(-2.6)	(-3.2)	(-2.7)	(-2.9)
	Q	α	-0.47	-0.45	-0.42	-0.58	-0.44	-0.64
			(-1.8)	(-1.9)	(-2.0)	(-2.4)	(-2.0)	(-2.5)
	FF5	α	-0.45	-0.41	-0.35	-0.53	-0.44	-0.55
			(-1.9)	(-1.7)	(-1.9)	(-2.2)	(-2.0)	(-2.3)
		β^{MKT}	0.10	0.07	0.09	0.10	0.03	0.07
			(1.9)	(1.4)	(2.0)	(2.0)	(1.0)	(1.4)
		β^{SMB}	-0.07	-0.09	-0.08	-0.11	0.04	-0.18
			(-0.7)	(-0.7)	(-0.9)	(-0.9)	(0.3)	(-1.5)
		β^{HML}	0.37	0.45	0.52	0.46	0.24	0.45
			(2.4)	(2.4)	(2.8)	(2.0)	(2.7)	(2.0)
		β^{RMW}	-0.10	-0.05	-0.09	-0.10	0.08	-0.15
			(-0.5)	(-0.2)	(-0.4)	(-0.5)	(0.5)	(-0.5)
		β^{CMA}	-0.29	-0.35	-0.59	-0.48	-0.32	-0.36
			(-1.0)	(-1.5)	(-2.4)	(-1.8)	(-1.4)	(-1.2)

Appendix A. Data Appendix

A.1. Leveraged fund dataset

A.1.1. List of daily leveraged funds

To identify leveraged funds from the CRSP MFDB, we use the quarterly file to search for a) fund names associated with the two Lipper objective codes “DL” and “DSB” referring to “Diversified leveraged funds/Equity Leveraged Funds” and “Dedicated Short Bias Funds”, respectively, at any point of time since June 2006, or b) fund names that contain “2x”, “3x”, “5x”, which account for 2x, 3x, and any fund which contains a leverage amount ending in 5x (e.g. 1.25x or 2.5x), or c) fund names that contain both “Proshares” and “Ultra”. The resulting dataset has an initial list of 1441 unique fund names over the sample period. We use the fund name as the fund identifier because we find that when the underlying index changes or when the target leverage changes, the fund name almost always changes but the CRSP fund number stays the same.[59]

To ensure we capture all leveraged funds to have ever existed in the market, we cross validate this CRSP-based list with an alternative list retrieved from Bloomberg. The Bloomberg list is constructed via fund screening with the following filters: “Market Status”: Active, “Country of Domicile”: United States, “Leverage” equal to yes, “Rebalancing Frequency” equal to daily, N.A., or unknown, the last nine characters of “Ticker” equal to US equity, “Leverage Amount” larger or equal to 100 or N.A., and “Inception Date” earlier than January 1, 2017. The Bloomberg list contains 421 Bloomberg tickers, representing 421 eight-digit CUSIPs. We merge the CRSP list and the Bloomberg list first by the eight-digit CUSIP then by ticker. We find that there are only 33 tickers from the Bloomberg list that are not matched with our CRSP list.[60] Using these 33 tickers, we are able to add 27 CRSP fund names to our original CRSP list by searching the entire quarterly CRSP universe using either ticker or CUSIP. Our augmented CRSP list contains 1468 unique fund names. In contrast, there are 571 fund names in our initial CRSP list that are not captured by the Bloomberg list.[61]

[59]We also identify the handful of cases when the fund name stays the same in these cases, as described in the following paragraphs.

[60]Specifically, we first look for funds that appear in the Bloomberg list but not in the CRSP list by eight-digit CUSIP. Then, for these funds we further check whether they can be matched to funds in the CRSP list by ticker.

[61]The unique identifier, CRSP fund number, in CRSP MFDB can be matched with multiple eight-digit CUSIPs, tickers, and fund names over the fund’s history. We consider all fund names associated with a

We merge our augmented CRSP list with the quarterly CRSP file, the daily CRSP returns, and the monthly CRSP file for the sample period between 2006 and 2016. We remove fund names that do not track a constant multiple of an underlying benchmark index on a daily basis. These are typically ETNs that do not track the daily performance of an index (except for those offered by Velocity) or funds that do not have a constant leverage multiple. Our comprehensive list of daily leveraged funds contains 1005 CRSP fund names between 2006 and 2016.

A.1.2. Index Matching

We obtain the constant leverage multiple and the underlying index in two steps. First, if CRSP provides the NASDAQ ticker for a fund and the ticker has an active trading status according to Bloomberg, then we download the constant leverage multiple and the underlying index ticker from Bloomberg. It is important to emphasize that we only download information from Bloomberg for tickers that are currently traded as of March 1, 2017 when our data collection process finished. This is because Bloomberg information for historical (dead) funds is sparse and can be inaccurate, especially when the leverage or the benchmark index changes for the same ticker or CUSIP. Second, for the remaining funds, we manually collect the constant leverage multiple and the underlying index contained in the funds' investment prospectuses, filed pursuant to Securities Act Rule 485(a) from the SEC Edgar database.[62] Generally, the investment objective section of these documents contains the leverage multiple, the ticker or name of the underlying index, and the rebalancing frequency.[63]

We classify leveraged funds into one of the following asset classes: commodity, currency, equity, fixed income, international, and VIX, according to the asset class of their underlying benchmark index. In total, our dataset captures 942 funds tracking 123 benchmarks across major asset classes.

CRSP fund number that is linked to the Bloomberg list via the eight-digit CUSIPs or tickers as included in the Bloomberg list. The Bloomberg list tends to capture larger funds, although it misses out on historical CUSIP or ticker information and sometimes records only one class of shares by a fund, such as ProFunds: UltraBear Profunds; investor shares.

[62]We identify the first date and the last date appearing in CRSP for each fund name, which determines the time period we search for this information.

[63]During this process, we discover 18 instances when the underlying index changes but the fund names remain the same via the information provided by the SEC 485 filings. We list these instances in our Data Appendix. For example, the Direxion Shares ETF Trust: Direxion Daily Mid Cap Bear 3X Shares changed from tracking the Russell Mid Cap index to the S&P Mid Cap index on June 29, 2012.

A.1.3. Final Dataset

To ensure the accuracy of the funding costs we compute, for the main analysis in this paper, we focus on a final list of 678 domestic funds that track 70 clearly defined, and tradeble spot indexes, representing a total of 625,088 fund-day observations. First, we remove 28 fund names for which we cannot find index returns.[64] Second, we remove 41 fund names that track returns on futures contracts, such as commodity futures and VIX futures, because these benchmark returns are already levered returns. Third, to avoid measurement errors associated with trading nonsynchronicity, we remove 240 fund names that belong to the international or currency funds. Fourth, we remove 12 fund names associated with abnormally large tracking errors and 6 fund names associated with a low leverage multiple (i.e., 1.25x).

A.2. Risk-free rates

1. *T-bill1M*, or the 1-month Treasury bill rate, is downloaded from the St. Louis Fed, FRED database. Each day, the rate is typically released at 3:30 PM EST.

2. *GC repo*, or the generalized collateral repurchase (GC repo) rate, is downloaded from the New York Fed website[65]

   (a) "Since the late 1990s, the Open Market Trading Desk at the Federal Reserve Bank of New York has conducted a survey of primary dealers each morning covering their borrowing activity in the Treasury general collateral repurchase (repo) market on that day."

3. $EFFR$, or the effective fed funds rate, is downloaded from the New York Fed website[66]

   (a) The rate is released at 9:00 AM EST

   (b) The historical median $EFFR$ is available prior to 6/17/2015. The historical mean $EFFR$ is available prior to 3/1/2016, when the New York Fed decided to switch to publishing the median. We use the median $EFFR$ whenever possible, and fill in with the mean $EFFR$ for the period (inclusive) between 6/17/2015 and 3/1/2016

[64] E.g. some Rydex fixed income funds state they track the most recently issued long treasury bond without specifying the exact index.

[65] https://www.newyorkfed.org/markets/opolicy/operating_policy_180309

[66] https://www.newyorkfed.org/medialibrary/media/markets/EFFR-Data-070815.xlsx

4. If the risk-free rate for a trading day is missing, we use the 1-day lagged risk-free rate. In a few cases when the observations are missing for consecutive days, we backfill missing observations with the last available observation.

A.3. Funding condition proxies

1. TED, or the TED spread, is downloaded from the St. Louis Fed, FRED database (https://fred.stlouisfed.org/series/TEDRATE). The measure is the spread between the 3-month LIBOR and 3-month Treasury bill rate.

2. VIX is downloaded from the St. Louis Fed, FRED database. The VIX is the implied 30-day volatility of the S&P500 from at-the-money and out-of-money S&P500 options.

3. ICR, or the intermediary capital risk factor of He et al. (2017), is available at the daily, monthly, and quarterly frequency from the authors' website.

4. LEV, or the leverage factor of Adrian et al. (2014), is available at quarterly frequency from the authors' website.

A.4. Innovations in variables

1. We compute the innovations consistently in the following way that avoids forward-looking bias, similar to Boguth and Simutin (2018).

   (a) We estimate the innovations in all variables using an autoregressive model with 1 lag, i.e., AR(1). Depending on the data frequency, the 1 lag can mean 1 day, or 1 month.

   $$y_t = a + \rho y_{t-1} + \epsilon_t$$

   (b) For the given variable, the first estimation is done using data in the first year of the sample period. We then use the resulting residuals as the innovations for the first year.

   (c) At the end of each month t after the first year, we re-estimate the AR(1) model and use the resulting residuals for month t as the innovations for month t.

A.5. *Extending LCT* (β_{MF}^{MKT})

Our sample selection follows Boguth and Simutin (2018). We are required to link the CRSP Mutual Fund Database (CRSP MFDB) to the Thomson Financial Mutual Fund Holdings (s12) via the Wharton Research Data Services MFLINKS file.

1. We start with the quarterly CRSP mutual fund file. The resulting dataset should connect the crsp_fundno in CRSP MFDB to the wficn identifier in MFLINKs. We implement the following:

   (a) We use the crsp_obj_cd in conjunction with the si_obj_cd, and name searching to get a sample of diversified equity mutual funds that are actively managed.

      i. crsp_obj_cd and si_obj_cd

         A. Keep funds that are in 'EDC' or EDY'

         B. Next, remove funds that are 'EDYH' or 'EDYS'

         C. Finally, remove funds with si_obj_cd == 'OPI'

      ii. List of keywords to remove funds that are index and target date funds

         A. Words: 'index', 's&p', 'idx', 'dfa', 'program', 'etf', 'exchange traded', 'exchange-traded', 'target'

         B. Numbers: '2000', '2005', '2010', '2015', '2020', '2025', '2030', '2035', '2040', '2045', '2050', '2055', '2060', '2065', '2070', '2075'

      iii. Remove funds that were not 'EDC' or 'EDY' at any point in their lifetimes.

   (b) Next we get the wficn from the MFLINK1 file via merging by crsp_fundno. Here there is a slight issue that 4 out of 28841 crsp_fundno have multiple wficn, which we remove.

2. Next, we work from the Mutual Fund Holdings file. The resulting dataset is unique in wficn-month-PERMNO, and in the same month, makes wficn in MFLINKS and fundno in the Mutual Fund Holdings file one-to-one

   (a) First, filter out those with investment objective code (IOC), 1, 5, 6, and 7, International, Municipal Bonds, Bond & Preferred, and Balanced codes, respectively.

   (b) To prepare for the merge with MFLINK2, select the unique set of fundno-rdate-fdate from the full holdings data. Call this dataset the MFHoldingsKey

   (c) Merging the MFHoldingsKey with the MFLINK2 file

i. Use fundno-rdate-fdate triple to merge to get wficn and assets.

ii. To avoid stale data, pick out the first fdate for each fundno-rdate pair.

iii. When there is more than one rdate for each fundno-month, pick the most recent rdate.

iv. To make sure that wficn-rdate is unique, pick the fund that has the largest assets

(d) Use the MFHoldingsKey to subset of complete holdings data, using fundno-date.

(e) Link the CUSIP from the holdings file to NCUSIP from CRSP to get PERMNO each equity holding.

i. The merge is by CUSIP==NCUSIP for the same month (by rdate)

A. Next get the CFACSHR for the rdate and the fdate using CUSIP == NCUSIP

B. The adjustment to shares is: shares * CFACSHR_fdate / CFACSHR_rdate

ii. The correct historical holding value is based on shares * CFACSHR_fdate / CFACSHR_rdate * abs(PRC)

iii. The adjusted shares == 0 are replaced with the unadjusted shares

3. Finally, we replicate LCT with the following procedure, using the holdings file and the equity funds file.

(a) The finished file is holdings data that is unique in wficn-month-PERMNO. This file contains on average 122 holdings per wficn-month (month is based on the rdate)

(b) Evans (2010) incubation bias

i. We remove observations in which the quarter is before the quarter of the reported first offer date

ii. We remove observations with missing CRSP fund name

(c) LCT requires three months of reporting positions to calculate for a given month.

i. For month t, get the holdings (in dollars) as of the end of month t

ii. For month $t-1$, get the holdings as of the end of month $t-1$, adjusted for returns (i.e. $(1 + RET_t + DLRET_t)$) from month t

iii. For month $t-2$, get the holdings as of the end of month $t-2$, adjusted for cumulative returns (i.e. $(1+RET_t+DLRET_t)\times(1+RET_{t-1}+DLRET_{t-1})$) from month $t-1$ to t.

iv. Using the adjusted holdings values, aggregate by PERMNO, to get the total dollar holdings by active domestic equity mutual funds.

(d) Estimate for month t, individual betas for each PERMNO using daily returns within month t

i. Model: $R_{it} = \alpha_i + \beta_{i0} R_{Mkt,t} + \beta_{i1} R_{Mkt,t-1} + \beta_{i2}[(R_{Mkt,t-2} + R_{Mkt,t-3} + R_{Mkt,t-4})/3] + \epsilon_{it}$

ii. Estimated Beta: $\beta_i = \beta_{i0} + \beta_{i1} + \beta_{i2}$

iii. We require at least 10 non-missing returns for each PERMNO-month to estimate.

(e) For month t, $LCT = \sum_i \frac{holdings_i}{\sum_i holdings_i}\beta_i$

4. Our final procedure results in a 0.97 correlation with actual LCT downloaded from the authors' websites over 1980 to 2014. We use the last two years of our replication (2015 and 2016) to extend the actual LCT to 2016.

A.6. Betas and IVOL used as bivariate controls

The control (betas) variables used in our bivariate analysis are: β^{TED}, β^{VIX}, β^{LCT}, β^{LEV}, β^{ICR}, and $IVOL$. We compute a valid, based on filters, β for each PERMNO over the sample period, June 2006 to Dec. 2016.

1. β^{TED} is measured as the slope coefficient on the daily innovation in the TED spread (TED) from a 12-month rolling window regression of daily excess stock returns on contemporaneous MKT and TED innovations. We use 3-day moving averages for all variables, and require ≥ 180 observations in each window for a PERMNO to estimate β^{TED}.

2. β^{VIX} is measured as the slope coefficient on the change in the VIX index (VIX) from a 1-month rolling window regression of daily excess stock returns on contemporaneous MKT and VIX changes. We require ≥ 15 observations in a PERMNO-month to estimate a valid β^{VIX}.

3. β^{LCT} is measured as the slope coefficient on the monthly innovation in LCT (β^{MKT}_{MF}) from a 24-month rolling window regression of monthly excess stock returns on contemporaneous MKT and LCT innovations. We require ≥ 12 observations in each window for a PERMNO to estimate β^{LCT}.

4. β^{LEV} is measured as the slope coefficient on the Leverage (LEV) factor from a full sample regression of quarterly excess stock returns on contemporaneous MKT and LEV. Quarterly stock and market excess returns are computed by compounding monthly returns and risk free rates.

5. β^{ICR} is measured as the slope coefficient on the daily intermediary capital risk (ICR) factor from a 12-month rolling window regression of daily excess stock returns on contemporaneous MKT and ICR. We use 3-day moving averages for all variables, and require ≥ 180 observations in each window for a PERMNO to estimate β^{ICR}.

6. $IVOL$ is measured as the standard deviation of the residuals from a 1-month rolling window regression of daily excess stock returns on MKT, SMB, and HML. We require ≥ 15 observations in a PERMNO-month to estimate a valid $IVOL$.

A.7. Additional variable definitions

We compute month t market capitalization (MKTCAP) for firm i in the Large Cap sample as follows:

$$MKTCAP_{it} = abs(PRC_t) * SHROUT_t$$

We compute Amihud's illiquidity (ILLIQ) for firm i in the Liquid sample using moving 1 year windows for each month t. r_{id} and vol_{id} are the daily return and trading volume for firm i on day d.

$$ILLIQ_{it} = \frac{1}{T_t} \sum_{d=1}^{T_t} \frac{|r_{id}|}{vol_{id}}$$

We compute margin debt following Asness, Frazzini, Gormsen, and Pedersen (2018). The data is available for from 1959 to 2017, and is published on the NYSE website.[67] The market capitalization of NYSE firms is from the CRSP monthly file, using exchange code 1, and share code 10, 11, and 12.

[67] http://www.nyxdata.com/nysedata/asp/factbook/viewer_edition.asp?mode=table&key=3153&category=8

$$MD_t = \frac{NYSE\, margin\, debt_t}{Market\, capitalization\, of\, NYSE\, firms_t} * 100$$