Leverage Constraints and Asset Prices: Insights from Mutual Fund Risk Taking

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January 13, 2015

ABSTRACT

Prior theory suggests that time variation in the degree to which leverage constraints bind affects the pricing kernel. We propose a demand-based measure for this leverage constraint tightness by inverting the argument that constrained investors tilt their portfolios to riskier assets. We show that the average market beta of actively managed mutual funds – intermediaries facing leverage restrictions – captures their borrowing demand and thus the tightness of leverage constraints. Consistent with theory, it strongly predicts returns of the betting-against-beta portfolio, and is a priced risk factor in the cross-section of mutual funds and stocks. Funds with low exposure to the factor outperform high-exposure funds by more than 5% annually, and for stocks this difference reaches 7%. Our results show that the tightness of leverage constraints has important implications for asset prices.

Keywords: Leverage constraints, asset prices, betting-against-beta, mutual fund performance, cross-section of stock returns.

*We thank Hank Bessembinder, Scott Cederburg, Zhuo Chen, Jean-Sébastien Fontaine, Andrea Frazzini, Ruslan Goyenko, Marcin Kacperczyk, Andrew Karolyi, Andrea Lu, Tyler Muir, Lasse Pedersen, David Schreindorfer, Dimitri Vayanos, Sunil Wahal, and seminar participants at Arizona State University, the University of Oklahoma, and the 2014 University of Minnesota Junior Finance Conference for helpful comments. Boguth: W. P. Carey School of Business, Arizona State University, PO Box 873906, Tempe, AZ 85287-3906. Simutin: Rotman School of Management, University of Toronto, 105 St. George Street, Toronto ON, Canada, M5S 3E6.

A key assumption underlying the capital asset pricing model (CAPM) is that investors can use leverage to achieve the level of risk and return optimal for their preferences. If investors face binding leverage constraints, the Lagrange multiplier associated with the constraint enters the pricing kernel (Brunnermeier and Pedersen, 2009), and investors optimally deviate from holding the market portfolio and tilt their investments towards riskier assets (Frazzini and Pedersen, "FP", 2014).

Leverage constraints bind when more leverage is desired than available. Prior empirical work has proposed measures related to the supply of leverage, such as the cost or availability of borrowing.[1] However, supply considerations alone are insufficient to capture the degree to which leverage constraints bind if the demand for leverage also fluctuates. In this paper, we study the pricing implications of leverage constraints using a measure of revealed borrowing demand.

Our identification relies on financial intermediaries that are unaffected by fluctuations in the lending market: mutual funds. These investors face borrowing restrictions established by the Investment Company Act of 1940 and often self-impose stringent zero-leverage constraints.[2] As a result, supply-based measures such as the cost of borrowing do not directly apply to them. Because leverage restrictions shut down the supply channel, fluctuations in the demand for borrowing of mutual funds reveal the tightness of leverage constraints, a measure analogous to the theoretically priced Lagrange multiplier.

To quantify the borrowing demand, we build on the theory developed in FP and Alankar, Blaustein, and Scholes (2014), who suggest that mutual funds shift to riskier assets when leverage constraints bind. Inverting their reasoning, we argue that the observable risk taken on by mutual funds reveals their demand for borrowing and hence

[1] Existing proxies can be categorized into two coarse groups: (1) variables capturing the cost or availability of borrowing, such as the TED spread (FP), margin requirements (Gârleanu and Pedersen, 2011), and the leverage of broker-dealers (Adrian, Etula, and Muir, 2014), and (2) variables, such as the Treasury bond funding liquidity of Fontaine and Garcia (2012), which build on the arguments of Shleifer and Vishny (1997) and Gromb and Vayanos (2002) that arbitrage violations should be more numerous if arbitrageurs are borrowing-constrained.

[2] For example, Almazan, Brown, Carlson, and Chapman (2004) report that investment policies frequently do not permit borrowing, and less than 8% of all funds use leverage. Even funds that are not fully invested can face binding constraints since the unpredictable nature of both fund outflows and investment opportunities creates an incentive for precautionary cash holdings (Simutin, 2014).

the unobservable tightness of the constraint. To estimate this risk, we calculate the beta of the aggregate stock holdings of all actively managed equity funds.[3] We show that the average beta fluctuates significantly over time and correlates with existing measures of funding supply.

Our measure of leverage constraint tightness (LCT) strongly and significantly predicts returns of FP's betting-against-beta factor (BAB), which is long levered low-beta stocks and short de-levered high-beta stocks. Times of binding leverage constraints are followed by high BAB returns. Importantly, this positive relation is consistent with the theoretical prediction in FP, and contrasts with their empirical observation that the TED spread, a supply-based proxy for borrowing constraints, predicts BAB returns with a theoretically incorrect negative sign. LCT alone explains 19% of the variation in future annual BAB returns. The economic magnitude of this predictability is large: Following times of high LCT, the BAB portfolio delivers average returns of 1.70% per month, while it earns negative returns after low-LCT periods. Other proxies for funding conditions fail at robustly predicting BAB returns and explain less of their time-series variation.

Having established that the aggregate mutual fund beta is a theoretically and empirically compelling proxy for LCT, we turn to the pricing implications. Our first set of tests analyzes future performance of funds with different exposures to LCT. In particular, for each fund, we run rolling regressions of its excess returns on market excess returns and changes in LCT. We show that exposure to changes in LCT strongly and negatively predicts fund performance in the cross-section. The magnitude of the effect is economically large: During the period from 1988 to 2013, the decile of funds with the lowest exposure outperforms the one with the highest exposure by more than 0.40% per month after controlling for standard risk factors. The effect is not confined to extreme deciles; rather, fund returns decrease monotonically with LCT exposure.

The negative relation between LCT loadings and future fund performance remains

[3] Our focus on betas estimated from returns of risky assets rather than overall fund returns is consistent with the theory in FP, where an unconstrained investor prefers increasing risk through leverage instead of shifting to riskier holdings.

large in gross-of-fees returns, and is robust to controlling for fund characteristics and determinants of mutual fund performance from prior literature, and to alternative estimation approaches. For example, the difference in future returns of low- and high-exposure funds frequently exceeds 0.60% monthly in response to variations in portfolio formation methodology.

What drives the inverse relation between LCT exposures and future mutual fund returns? We hypothesize that it is due to the existence of a priced factor relating to leverage constraint tightness, as suggested in Brunnermeier and Pedersen (2009).[4] An asset that pays off when constraints tighten provides capital when it is most valuable and should carry a negative risk premium. If that is the case empirically, strong relative performance of funds with low LCT exposures may be viewed as compensation for leverage constraint tightness risk.

We begin the investigation of the risk-based explanation of mutual fund return forecastability by asking whether loadings on changes in LCT predict returns at the firm level. Following the same approach used with mutual funds, we run rolling stock-level regressions to obtain LCT loadings. We find that the estimated LCT exposures negatively predict stock returns in the cross-section. The difference in performance of firms with low and high loadings is 0.58% monthly and is statistically significant. This result is robust to standard risk-adjustments, to variations in portfolio formation and weighting methodology, and to controlling for firm characteristics in Fama and MacBeth (1973) regressions.

Following the procedure in Fama and French (1993), we construct a leverage constraint tightness risk factor based on the cross-sectional exposure to LCT. This factor provides a risk-return tradeoff that compares favorably with existing factors. Its monthly Sharpe ratio of 0.16 exceeds those of market, size, value, momentum, and liquidity factors in our sample. We show that controlling for loadings on the leverage

[4] LCT might be priced in the cross-section of stocks for two reasons. First, mutual funds could be the marginal investors in the stocks. Second, while obtained from mutual funds, LCT could measure the economy-wide demand for leverage. Of course, not all investors can take on market betas larger than one; less constrained investors such as hedge funds can meet their leverage demand by borrowing.

constraint tightness risk factor attenuates the spread in returns of the LCT exposure-sorted mutual fund portfolios by approximately one half. A significant component of the superior performance of the low-exposure funds is thus inherited from stocks with high leverage constraint tightness risk. However, the unexplained part of the return spread remains economically and statistically significant, suggesting that another force, such as mutual fund-specific risk or managerial skill, contributes to the differences in performance.

Literature

Our central contribution is to the literature studying the effects of leverage constraints on asset prices. Early research derives equilibrium pricing implications when borrowing is costly (Brennan, 1971) or unavailable (Black, 1972) in static models. Our proxy is based on theoretical results in FP, who model borrowing constraints that vary across investors and over time. In their model, when explicit leverage is unavailable, investors substitute the higher implicit leverage embedded in high-beta assets.

Brunnermeier and Pedersen (2009) and Gârleanu and Pedersen (2011) show that funding liquidity affects asset prices. In particular, Brunnermeier and Pedersen (2009) show that even for risk-neutral investors, funding conditions can enter the pricing kernel. In their model, the Lagrange multiplier on the funding restriction places a higher value on states with tighter constraints. This mechanism establishes LCT as a risk factor, and covariation with this factor is priced negatively. Our empirical results are consistent with this theory.

Fontaine, Garcia, and Gungor (2014) find that a funding liquidity factor derived from the U.S. Treasury bonds (Fontaine and Garcia, 2012) is priced in the cross-section when the test assets are portfolios sorted on individual stocks' market liquidity measures. In contrast, our proxy appears in the cross-section of mutual funds and individual stocks, and is empirically only weakly related to market liquidity risk.

Chen and Lu (2013) refine FP's BAB factor by identifying stocks that are a priori more exposed to funding conditions. They show that exposure to their factor is related to hedge fund performance, but they argue that it is driven by managerial ability to time funding liquidity, rather than by risk. That hedge funds are affected by funding liquidity is not unexpected since they actively utilize leverage (Ang, Gorovyy, and van Inwegen, 2011). Our measure suggests that the tightness of leverage constraints is of high importance even for more conservative investors who are constrained from engaging in explicit leverage.

Adrian, Etula, and Muir (2014) empirically test the intermediary-based asset pricing theory of He and Krishnamurthy (2013). While mutual funds can be considered financial intermediaries, the equity capital constraints or the borrowing capacity of He and Krishnamurthy (2013) do not apply to mutual funds. In their tests, Adrian, Etula, and Muir (2014) show that the leverage of security broker-dealers is a promising candidate for the stochastic discount factor, successfully pricing a variety of stock and bond portfolios. Importantly, a main determinant of their leverage measure is short-term collateralized borrowing, which is ultimately tied to borrowing availability. We measure the unobservable tightness of leverage constraints, which for mutual funds can be binding even if borrowing was available to other market participants.

Our core analysis focuses on mutual funds. The agency implications of delegated money management have attracted considerable attention. Roll (1992), Brennan (1993), Baker, Bradley, and Wurgler (2011), Buffa, Vayanos, and Woolley (2014), and Christoffersen and Simutin (2014) show that benchmarking performance leads asset managers to increase market risk of their investments. Alankar, Blaustein, and Scholes (2014) generalize Roll (1992) by adding a leverage constraint in form of a minimum cash level. In their model, similar to FP, managers buy stocks with higher volatility than that of the benchmark to relax their constraint and to minimize the tracking error. Their empirical analysis focuses on the implications of the tracking error objective and does not consider time-variation in the degree to which the leverage constraint binds.

A separate line of mutual fund research has studied performance predictability of mutual funds. Most prominently, industry concentration of fund holdings, the extent of portfolio adjustments between reporting periods, and deviations from a benchmark portfolio have been linked to future fund performance (Kacperczyk, Sialm, and Zheng, 2005, 2008, Cremers and Petajisto, 2009, Amihud and Goyenko, 2013). Our focus on changes in risk-taking of the aggregate mutual fund complements the study of Huang, Sialm, and Zhang (2011), that analyzes risk-shifting in individual funds. Also related is the work of Dong, Feng, and Sadka (2014), who find that funds' loadings on market liquidity predict fund returns, which the authors attribute to managerial skill. We contribute to this strand of research by showing that exposure to changes in the degree to which leverage constraints bind is an important determinant of the cross-section of mutual fund performance.

I. Leverage Constraint Tightness

We introduce a theoretically motivated measure of leverage constraint tightness. FP and Alankar, Blaustein, and Scholes (2014) suggest that investors who cannot increase explicit leverage due to binding borrowing constraints shift their portfolio to riskier securities, thus utilizing the leverage embedded in high-beta assets. Reversing the theoretical argument suggests that the observable risk taken on by mutual funds can capture unobservable LCT. Motivated by this logic, we proxy for LCT by the market risk of the holdings of the aggregate mutual fund. We show empirically that our measure of LCT co-moves with known proxies for funding conditions, and, consistent with theory, robustly predicts returns of the BAB factor.

A. Data and the Aggregate Mutual Fund Beta

We obtain fund returns, investment objectives, fees, total net assets, and other fund characteristics from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free Mutual Fund Database. We use the Wharton Research Data Services MFLINKS file to merge this database with the Thomson Financial Mutual Fund Holdings dataset, which contains information on stock positions of funds disclosed in the 13F filings (Wermers, 2000). We limit our sample to diversified domestic equity mutual funds that are actively managed. Following Elton, Gruber, and Blake (2001) and Kacperczyk, Sialm, and Zheng (2008), we exclude funds with total net assets of less than $15 million and funds that hold on average less than 80% of assets in equity. We address Evans (2010) incubation bias by eliminating observations preceding the fund's starting year as reported in CRSP, and combine multiple share classes into a single fund. As in Amihud and Goyenko (2013), we arrive at the 1988-2013 sample after additionally deleting funds with missing names in CRSP.

We aggregate the holdings of all funds in our sample. Since holdings are disclosed only periodically, we infer fund positions between disclosures by assuming that they actively change only on portfolio report dates.[5] In particular, we calculate the holdings of the "aggregate" mutual fund at the beginning of month t as the sum of (i) the holdings of all funds in our sample that disclosed at the end of month $t-1$, (ii) the holdings of funds that disclosed at the end of month $t-2$, adjusted for the stock returns in month $t-1$, and (iii) holdings disclosed in $t-3$, adjusted for the cumulative stock returns in months $t-2$ and $t-1$. For each month t, we then use daily returns of this aggregate mutual fund portfolio within the month to estimate market beta, using the standard market model regression with one Dimson (1979) lag.

We estimate beta from returns of mutual fund holdings of risky assets rather than from total fund returns. The difference between the two measures is largely due to cash holdings and unobservable intermediate trading. This approach is consistent with the theory in FP that concerns the risk of asset holdings, not the overall portfolio risk.[6]

Figure 1 shows the time series of the aggregate mutual fund beta, smoothed over three months, and provides summary statistics. The average mutual fund beta is 1.07, consistent with the numbers reported in FP. Importantly, the measure exhibits mean-

[5]The U.S. Securities and Exchange Commission mandated quarterly disclosure of portfolio holdings starting in May 2004. Nonetheless, and consistent with the observation of Kacperczyk, Sialm, and Zheng (2008), most funds disclose holdings quarterly throughout our sample. Of the funds in our study that disclosed their holdings at least once in the previous 12 months, 80% did so in the preceding quarter.

[6]While this distinction is important theoretically, the empirical differences for our application are small since mutual funds, in aggregate, have a very stable cash-to-assets ratio. In untabulated analysis we reaffirm our main results with an LCT measure obtained from fund returns. Since daily fund returns are only available since September 1998, the resulting sample is significantly shorter.

ingful time variation. The standard deviation is 0.09, and the 10th and 90th percentiles are 0.99 and 1.19, respectively. The volatility of the aggregate beta is decreasing over time. This decline is consistent with the growth of the mutual fund industry, as aggregate mutual fund holdings make up a growing component of the market portfolio. The decrease in volatility does not affect our key tests because they are conditional in nature, using rolling windows of observations.[7]

Interestingly, while prior literature provides strong evidence that funding liquidity dried up during the financial crisis of 2008, the aggregate mutual fund beta declined and remained low during this period. Our interpretation of mutual fund beta as borrowing demand is consistent with this evidence, since uncertainty and risk in the market were also at all-time highs. All else equal, the optimal portfolio leverage for risk-averse, long-only investors such as mutual funds declines with volatility, implying a decrease in borrowing demand.

B. Aggregate Mutual Fund Beta and Funding Conditions

The theoretical link between aggregate mutual fund beta and leverage constraint tightness is well-motivated. We now study the empirical relation between our LCT measure and know proxies for funding conditions.

We consider five proxies: broker-dealer asset growth, broker-dealer leverage, bond-implied funding liquidity, the TED spread, and the VIX index. Adrian and Shin (2010) suggest that broker-dealers' asset growth corresponds to changes in their debt capacity. Since financial intermediaries manage their value-at-risk, asset growth is immediately followed by active balance sheet adjustments that result in a higher overall leverage. Adrian, Etula, and Muir (2014) follow this idea by proposing the broker-dealers' leverage factor. Fontaine and Garcia (2012) measure funding illiquidity from the cross-section of Treasury securities. The TED spread, the difference between LIBOR and T-bills rate, is frequently used to proxy for borrowing cost (e.g., Gârleanu and

[7]For the unconditional analysis, we confirm robustness to normalizing observations by their conditional standard deviation estimated from a linear trend.

Pedersen, 2011, FP). Lastly, funding conditions change with aggregate uncertainty, as proxied by the VIX (Ang, Gorovyy, and van Inwegen, 2011).

We are interested in how shocks to funding liquidity relate to LCT. Since both broker-dealer asset growth and leverage are available at a quarterly frequency, we use the last observation in each quarter for the monthly variables. Shocks to our measure are the changes in LCT relative to three months earlier. The broker-dealer leverage factor in Adrian, Etula, and Muir (2014) is already differenced, as is the Treasury security-based funding liquidity factor used by Fontaine, Garcia, and Gungor (2014). For the remaining variables, we define shocks as $AR(1)$ residuals. We sign all proxies so that positive shocks indicate worsening of borrowing conditions.

Table 1 shows the pairwise correlations between shocks to funding liquidity and LCT. Our measure is significantly and positively correlated with the negative broker-dealer asset growth (0.23) and with the bond liquidity factor (0.18). The correlation with the negative broker-dealer leverage factor is sizable, but statistically insignificant (0.08). These three measures suggest that increases in our LCT proxy are associated with deteriorating borrowing conditions. LCT does not correlate with the TED spread. This is not surprising, since the TED spread measures the cost of borrowing, which does not directly impact mutual funds.

The negative correlation with VIX is particularly revealing, since higher aggregate uncertainty has two opposing effects. On the one hand, uncertainty decreases funding availability and makes it more costly, seemingly tightening leverage constraints.[8] On the other hand, investors actively managing overall portfolio risk want to reduce leverage in times of heightened aggregate volatility, thereby lowering the desire for borrowing. The negative correlation with VIX is therefore consistent with our demand-driven measure of LCT. Overall, the evidence suggests that the aggregate mutual fund beta is a compelling empirical proxy for the degree to which leverage constraints bind.

[8]For example, Ang, Gorovyy, and van Inwegen (2011) show that the leverage of hedge funds in negatively related to the VIX.

C. Leverage Constraint Tightness and Betting-Against-Beta Profits

The relation between LCT and BAB warrants a more detailed discussion. The model of FP predicts that when leverage constraints tighten, the contemporaneous realized BAB return is negative (their equation 11), and the required future BAB premium increases (their equation 12). Consistent with the first prediction, they show empirically that changes in the TED spread are negatively related to the contemporaneous BAB return. But, contrary to the second prediction, the level of the TED spread forecasts BAB negatively. We now test these hypotheses using our LCT measure.[9]

We show in Table 2 that when LCT is used to measure leverage constraints, the empirical evidence supports both of the theoretical predictions in FP. Panel A presents regressions in which the dependent variable is the BAB return over one, six, and 12 months, expressed in percent monthly. The explanatory variables are contemporaneous changes in LCT or its lagged monthly level. We also consider the 6 and 12 months moving averages of LCT to reduce estimation noise.

Consistent with the first prediction, the contemporaneous change in LCT is negatively related to the BAB return.[10] More importantly, the level of our LCT proxy is positively related to future BAB returns, in line with the second prediction of FP. The predictive power is particularly pronounced when we use moving averages to smooth the LCT estimates. All coefficients are significantly positive, and the R^2 approaches 20% for 12-month-ahead regressions.

Panel B of the table illustrates the economic magnitudes of these relations. We split our sample of 312 month into three groups of 104 months each by the explanatory variables. The contemporaneous return of the BAB factor in the tercile of months with the lowest changes (i.e., the biggest declines) in LCT is 1.59%, while it is only 0.21%

[9]We follow the methodology in FP to extend the BAB factor until 2013. The correlation of our factor with the data made available by Andrea Frazzini is 0.99.

[10]Caution is warranted in the interpretation of this result. The change in the risk of a buy-and-hold portfolio is mechanically linked to BAB returns. If low-beta stocks have relatively high returns, their weight increases in a passive portfolio, leading to a decline in portfolio risk. In untabulated results, we confirm robustness of this finding when LCT is measured using individual stock betas, weighted by the beginning-of-month portfolio weights.

when LCT increases the most. Following times of nonbinding constraints (low LCT), the future one-month BAB return is 0.72%, while it is nearly double that, 1.31%, after periods of tight leverage constraints. Longer-horizon BAB returns relate even stronger to lagged LCT. For example, the average BAB return during one year following months with low LCT is negative at -0.20% monthly, while it is 1.67% after high-LCT periods. These results are robust when we use the one-month LCT or the smoothed 6- and 12-month measures. In all cases, the difference in BAB returns following high-tercile versus low-tercile LCT realizations is around 0.60% at the one month horizon and 1.80% monthly at an annual horizon.

In Table 3, we compare the ability of LCT and funding liquidity measures to predict BAB returns. Of all proxies, LCT yields the highest univariate R^2 and remains a significant and powerful predictor in multivariate regressions. All other variables are either insignificant, or enter with a theoretically incorrect sign.

The strong predictability of BAB provides empirical support to the theoretical predictions of FP and confirms the validity of our LCT proxy. It is also important because BAB is related to estimates of the price of risk from cross-sectional Fama and MacBeth (1973) regressions. Having a better understanding of the determinants of the cross-sectional price of risk can have implications for interpreting asset pricing tests.

D. Does the Aggregate Mutual Fund Beta Measure Leverage Constraints?

Our empirical analysis builds on the conjecture that aggregate mutual fund beta captures the tightness of leverage constraints. The correlations of our LCT measure with funding conditions and the success of LCT at predicting BAB factor returns provide evidence of the empirical validity of our proxy. However, aggregate mutual fund beta can change for reasons seemingly unrelated to the tightness of leverage constraints.

To understand how alternative economic mechanisms affect our LCT measure, it is crucial to distinguish arguments that predict changes in risk of the overall portfolio from arguments about the beta of risky asset holdings. For example, changes in managerial preferences as well as attempts to time the market or its volatility can all affect the optimal overall portfolio risk of mutual funds.[11] At the same time, these arguments make no predictions about the beta of the risky assets of unconstrained investors. As long as the market risk premium is larger than the cross-sectional reward for taking on an additional unit of beta risk, as is consistent with empirical evidence, investors will always prefer a levered investment in the market to an unlevered allocation in high-beta stocks.[12] As a result, managers who tilt their portfolios to high-beta stocks in anticipation of good market conditions must be constrained; if managers were unconstrained, they would have increased risk through borrowing instead. In other words, for any theory that makes predictions about overall portfolio risk, an increase in beta of risky asset holdings will correspond to tighter leverage constraints.[13]

Why might the beta of risky asset holdings vary over time? In addition to leverage constraints, at least two economic mechanisms make predictions about the beta of risky asset holdings. First, risk changes could be a response to mutual fund flows if managers follow an optimal liquidation policy (Scholes, 2000). This policy suggests that mutual funds should sell assets in order of decreasing liquidity to meet redemptions: first reduce cash holdings, then sell the most liquid assets, which typically have low betas, and only as a last resort sell illiquid, high-beta assets. Importantly, this pecking order theory assumes leverage constraints, and the optimal liquidation policy would change if redemptions could simply be met by moving into negative cash holdings. More generally, for our interpretation of mutual fund beta as a measure of LCT it is irrelevant whether funds actively buy higher-beta assets or sell lower-beta assets as

[11]In untabulated results, we confirm that the aggregate mutual fund beta is insignificantly related to market returns. It does negatively predict market volatility in univariate regressions, but not after controlling for lagged market volatility. These results are consistent with the lack of managerial timing skills documented in the mutual fund literature (e.g., Henriksson, 1984, Daniel, Grinblatt, Titman, and Wermers, 1997).

[12]Under the CAPM, the market risk premium and the cross-sectional beta risk premium are identical. However, there is abundant empirical support consistent with the theoretical prediction in FP that the price of risk estimated from the cross-section is smaller than the time-series average market excess return. See, for example, Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), and Fama and French (1992).

[13]If beta instead measure investment opportunities, the theoretical asset pricing implications would be opposite. In an intertemporal CAPM setting with time-varying first and second moments, risk-averse investors want to increase their risk exposure as a response to state variables that predict good times – high market returns or low market volatility. In the cross-section, exposure to these state variables should be positively priced. By contrast, if beta increases in response to changes in the tightness of leverage constraints, its price should be negative. The empirical findings in this paper strongly support the latter interpretation.

leverage constraints become more binding.

Second, managers might try to time the relative performance of high- and low-beta stocks that is unrelated to overall market timing. For example, if high-beta stocks on average have positive alphas relative to the benchmark model, managers should increase the average beta of their holdings. The common theories generating these predictions rely on borrowing frictions: FP model margin requirements and Hong and Sraer (2014) rely on short-selling constraints. Equally important, our empirical evidence strongly contradicts this interpretation. A high beta of mutual fund holdings is followed by low returns of high-beta assets.

Overall, the evidence strongly supports our interpretation of aggregate mutual fund beta. We cannot exclude that for some stock-picking managers the beta of equity holdings is not a first-order concern. However, the systematic forces that affect risk of mutual fund holdings are related to the degree to which leverage constraints bind.

II. Leverage Constraints and Mutual Fund Performance

In this section, we show that leverage constraint tightness is priced in the cross-section of mutual funds. We first obtain LCT loadings for each mutual fund from rolling time-series regressions of fund excess returns on market excess returns and changes in LCT. Next, we sort funds into portfolios to show that LCT risk loadings forecast mutual fund returns. Our main finding is that fund performance is strongly and negatively predicted by exposure to innovations in LCT, suggesting a risk factor as in Brunnermeier and Pedersen (2009). The economic magnitude of the predictability is large, about 5% annually, and remains robust after controlling for existing predictors of fund performance and measures of managerial skill. By contrast, loadings on proxies for funding conditions from prior literature do not predict fund returns.

A. Mutual Fund Performance

We obtain loadings β^{LCT} on our proxy for leverage constraint tightness from rolling regressions. In particular, for each month t and for each fund i we estimate

$$R^e_{i,\tau} = \alpha_{i,t} + \beta^{\text{MKT}}_{i,t} R^e_{M,\tau} + \beta^{\text{LCT}}_{i,t} \Delta^{\text{LCT}}_{\tau} + \varepsilon_{i,\tau} \qquad \tau \in \{t-11, t\}, \tag{1}$$

where $R^e_{i,\tau}$ and $R^e_{M,\tau}$ are excess returns of fund i and the market in month τ, and $\Delta^{\text{LCT}}_{\tau} = \text{LCT}_{\tau} - \text{LCT}_{\tau-1}$ is the change in leverage constraint tightness. To obtain meaningful risk loadings, we require each fund to have non-missing returns in all months of the estimation period.

At the end of each month t, we rank funds into deciles by loadings on leverage constraint tightness, $\beta^{\text{LCT}}_{i,t}$, and compute the equal-weighted average return of each group in month $t+1$. Panel A of Table 4 summarizes the net-of-expenses performance of the decile portfolios and shows the difference in performance of high- and low-β^{LCT} funds.[14] We calculate simple excess returns as well as alphas from the market model, the Carhart (1997) four-factor model, as well as a five-factor factor model that augments the Carhart (1997) model with the Pástor and Stambaugh (2003) liquidity factor.[15]

We find that raw and risk-adjusted future fund returns decline monotonically with LCT loadings. The magnitude of the effect is economically large. For example, the decile of funds with the lowest LCT exposure generates monthly excess returns of 0.76%, while the highest decile earns just 0.49%. The performance differential amplifies after risk adjustment. In particular, the low-β^{LCT} generates a positive four-factor alpha of 0.11% monthly, and the high-exposure group performs the worst, earning -0.33%. The difference in returns of the two groups, at 0.44% per month ($t = 2.97$) is very large, given that we are comparing portfolios of diversified mutual funds. Most studies of mutual fund performance predictability document considerably smaller return differentials.[16] The last five columns of Table 4 show unconditional loadings on the five factors. While

[14] Of course, mutual funds cannot be shorted, so the return difference should not be interpreted as a return an investor can generate by buying one set of funds and selling another. Rather, a correct interpretation is how much higher a return an investor would generate by buying the low decile rather than the high decile.

[15] We also test our results against the permanent-variable price-impact factor of Sadka (2006) and find a weak, but positive, relationship between LCT and market liquidity loadings. We report the results using the Pástor and Stambaugh (2003) measure because Sadka's factor is available only until 2010.

[16] For example, the spread in four-factor alphas, calculated using net-of-fees returns, of portfolios sorted by industry concentration ratio, return gap, active share, and R-squared range between 0.17% and 0.32% per month (Kacperczyk, Sialm, and Zheng, 2005, 2008, Cremers and Petajisto, 2009, Amihud and Goyenko, 2013, respectively).

the low-high portfolio loads positively on the value factor, it has negative exposures to market, size, and momentum factors, clarifying why its risk-adjusted returns exceed raw returns.

Investors are primarily concerned with fund performance net-of-expenses, but examining gross-of-fees performance can help better assess managerial abilities if skilled managers charge higher expenses (Berk and Green, 2004). Panel B of Table 4 shows that the difference in future gross-of-fees performance of the low and high decile portfolios is equally large as in the net-of-expenses case.

To study whether the negative relation between β^{LCT} and future fund performance is different for funds of different size, we group funds into halves by total net assets and then assign them into β^{LCT} deciles within each group. Panels C and D of Table 4 show that the difference in returns of low- and high-β^{LCT} funds is strong among funds with above- and below-median fund size. For example, the difference in four-factor alphas of funds with low and high LCT betas is 0.50% monthly for small funds and lower but still statistically and economically significant for large funds (0.38%).

In Panel E, we extend the rolling window used to calculate LCT loadings to 24 months. Doing so reduces estimation noise but comes at the expense of yielding a stale estimate as short-term fluctuations in LCT loadings average out over longer horizons. This concern is particularly relevant for mutual funds, because on average funds turn over their entire portfolio about once every year (Kacperczyk, Sialm, and Zheng, 2005). Nonetheless, our results remain strong.

Lastly, in Panels F and G we calculate loadings from single-factor regressions that omit the market factor. Omitting the market factor reduces the noise in estimating β^{LCT} and is consistent with the approach used in Adrian, Etula, and Muir (2014). The results from this estimation are even more pronounced. The spread in four-factor alphas reaches 0.60%. Overall, the results summarized in Table 4 paint a striking picture of a strong inverse relation between funds' exposures to changes in leverage constraint tightness and future fund performance.

B. Back-tested Mutual Fund Performance

The risk loadings obtained from regression (1) can suffer from potentially significant estimation errors. As a result, the top and bottom β^{LCT} deciles might be populated by not just the funds with the highest and lowest LCT loadings, but also by funds with the highest estimation errors. One way to reduce the errors is to use longer windows in the estimation, as in Panels E and G in Table 4. Another way to alleviate the problem is to use the simple back-testing strategy proposed by Mamaysky, Spiegel, and Zhang (2008). They require the statistical sorting variable, in our case β^{LCT}, to exhibit some past predictive success for a particular fund before it is used to make predictions for that fund in the current period.

We implement this back-testing strategy following Kacperczyk, Sialm, and Zheng (2008), Dong and Massa (2013) and Dong, Feng, and Sadka (2014). In particular, we first rank funds based on β^{LCT} at the end of month t, just as in the sorting procedure underlying the results in Table 4. However, instead of investing in this portfolio in month $t+1$, we use this month to identify the funds for which measurement errors were likely significant. The theoretical predictions and our empirical analysis suggest that LCT exposure should be negatively related to future returns. For funds with above-average LCT betas, we therefore expect below-average returns. If instead we observe above-average returns, there is an increased chance that the LCT beta was affected by estimation error. Consequently, we only keep funds whose demeaned estimated LCT loading and the demeaned return in excess of the market have opposite signs, and hold the portfolio in month $t + 2$.

Table 5 summarizes the results of the back-testing strategy. As in Table 4, LCT exposure is negatively related to future returns, and risk adjustment magnifies this effect. However, the back-testing procedure yields a considerably wider spread in future returns of the β^{LCT}-sorted portfolios. Panel A shows that the spread expands by around 0.20% monthly relative to the case without back-testing. For example, the difference in excess returns of the low- and high-exposure portfolios reaches 0.51% monthly, economically very large and statistically significant ($t = 2.94$). Standard risk adjustment again amplifies this difference, yielding four-factor alphas of 0.63% monthly. Funds in the low-exposure decile generate alphas that are not just positive but also statistically significant at the 5% level. The remaining Panels of Table 5 mirror those in Table 4, highlighting the robust nature of the negative relation between LCT betas and future fund performance.

Figure 2 plots four-factor alphas of the β^{LCT}-sorted portfolios. The left (red) bars show performance measures obtained from the simple sort, and the right (blue) bars from the back-tested strategy. For both approaches, the alpha decreases monotonically with LCT exposure. The back-testing increases the alphas of the first four deciles, and decreases the alphas of the remaining groups. As expected, the effects of back-testing are generally largest in the more extreme portfolios.

C. Robustness to Other Predictors of Fund Performance

Prior literature has identified several measures of managerial skill that predict mutual fund performance. The most prominent of these variables compare how fund holdings differ from holdings of a benchmark portfolio (e.g., industry concentration ratio of Kacperczyk, Sialm, and Zheng, 2005, and active share of Cremers and Petajisto, 2009), or compare fund returns against benchmark returns (e.g., return gap of Kacperczyk, Sialm, and Zheng, 2008, and R-squared of Amihud and Goyenko, 2013).

The theoretical motivation for our measure and its relation to future fund performance is entirely different from these papers. We therefore do not expect that LCT loadings relate to these known measures of skill. Nonetheless, to verify robustness of our results, we now investigate whether the ability of LCT loadings to predict fund performance varies among subsets of funds that differ in managerial skill. In addition to the variables just mentioned, we consider prior fund return (Hendricks, Patel, and Zeckhauser, 1993, Bollen and Busse, 2004) and fund turnover (Pástor, Stambaugh, and Taylor, 2014).

We group funds into halves by each of the skill measures and assign them into β^{LCT}

deciles within each group. Table 6 summarizes the differences in four-factor alphas of the low- and high-β^{LCT} decile portfolios for the subsets of funds with above- and below-median skill measures. We show results before and after applying the back-testing methodology. The results convincingly indicate that irrespective of whether the managers are inferred to be skilled, funds with low exposure to LCT innovations outperform high-exposure funds by a significant margin, between 0.22% and 0.59% monthly. The predictability of mutual fund performance that we uncover is thus distinct from the results documented in the prior literature on managerial skill.

III. Leverage Constraints and Stock Returns

The strong negative link between mutual funds' return sensitivity to changes in the tightness of leverage constraints and future performance can have two primary causes. First, if LCT is a priced risk factor in the cross-section of stocks, it would be natural that this factor is also relevant for mutual funds. Alternatively, some mutual funds might actively trade in response to and in expectation of changes in LCT, and the performance documented in the previous section can reflect a dimension of managerial skill.

This section shows that a significant component of mutual fund performance related to LCT exposure is inherited from the stocks they hold. Loadings on leverage constraint tightness forecast returns at the firm level, and a stock-based LCT risk factor helps to explain the mutual fund performance.[17]

A. Cross-Sectional Return Predictability

We obtain monthly risk loadings β^{LCT} as slope coefficients from rolling time-series regressions of individual security excess returns on market excess returns and changes in LCT, as in Equation (1).[18] We form portfolios based on the estimated β^{LCT} and examine

[17] Using firm-level data alleviates the critique of Lewellen, Nagel, and Shanken (2010), who argue that the selection of test assets matters for cross-sectional tests of asset pricing models. Ang, Liu, and Schwarz (2010) also emphasize the use of individual stock return data because of the information contained in the cross-section of risk loading.

[18] Our sample consists of all common stocks on CRSP listed on the NYSE, Amex, or NASDAQ. Our results are robust to excluding financial firms and utilities and to imposing a minimum price filter.

returns in the month following the estimation period.

We summarize the results of this portfolio analysis in Table 7. Panel A shows that the value-weighted quintile of stocks with low LCT loadings generates excess returns of 0.94% monthly, while the quintile with high loadings earns just 0.39%. The difference of 0.55% is economically large and statistically significant (t=2.53). The next three columns show alphas estimated from the CAPM, the Carhart (1997) four-factor model, and the five factor model that includes the Pástor and Stambaugh (2003) liquidity factor. These alphas paint a similar picture: Alphas are positive for the low-exposure portfolio, ranging from 0.14% to 0.24% monthly, and are strongly negative for the high-exposure portfolio, between -0.38% and -0.43%. The difference, ranging from 0.57% to 0.65%, is always statistically significant.

The last five columns contain the risk loadings from the five-factor model. There is some evidence that stocks with higher measurement error, such as those with high market beta and small market capitalization, are overrepresented in the extreme portfolios. Importantly, for the low-high hedge portfolio, risk loadings on market, size, value, and momentum factors are small and statistically insignificant, suggesting that leverage constraint tightness is largely orthogonal to standard risk factors. Our hedge portfolio does load negatively on the Pástor and Stambaugh (2003) liquidity factor, slightly raising the alpha.[19]

In the remaining panels, we evaluate robustness by varying portfolio formation and weighting methodology. We repeat the analysis for the low-high portfolio using equal-weighted returns (Panel B), as well as splitting the sample in halves (C and D) or deciles (E and F) instead of quintiles. In all cases, the difference portfolio has economically large and statistically significant returns.

One drawback of the portfolio sorts is that they do not allow for a multivariate analysis. Many characteristics have been shown to successfully predict stock returns,

[19]Brunnermeier and Pedersen (2009) show theoretically that funding conditions and market liquidity are tightly linked. In international data, Karolyi, Lee, and van Dijk (2012) find that demand-side factors such as correlated trading behavior or investor sentiment explain commonality in market liquidity better than supply-side factors such as the funding liquidity of financial intermediaries.

including market capitalization, the ratio of book equity to market equity, past stock returns, asset growth, and gross profitability.[20] We use Fama and MacBeth (1973) regressions to investigate whether these characteristics subsume the predictive ability of LCT exposure.

Table 8 presents the results. Regression (1) confirms the negative predictive power of β^{LCT}. The estimated price of LCT risk is negative at -0.24% monthly. Given the time-series average of the cross-sectional standard deviation of estimated loadings (0.74, untabulated), this coefficient implies that a one standard deviation increase in LCT risk results in a 0.18% decrease in future monthly return. The t-statistic on the coefficient exceeds 4, clearing not only conventional levels of significance, but also the more stringent hurdle suggested by Harvey, Liu, and Zhu (2014) to account for data mining. In the remaining regressions, we augment β^{LCT} by characteristics. In all cases, our coefficient of interest remains significantly negative. The point estimate changes only slightly across specifications.[21] Overall, the results from the portfolio sorts and Fama-MacBeth regressions provide strong evidence that LCT loadings are an important determinant of the cross-section of stock returns, and are distinct from the commonly considered predictors.

B. A Leverage Constraint Tightness Risk Factor

Given the evidence that leverage constraint tightness is priced in the cross-section of stock returns, we now revisit the performance predictability of mutual funds. In particular, we ask if the large return differential attributed to LCT exposure of mutual funds simply reflects the risk premium from the stocks they hold, or whether an alternative, mutual fund-specific explanation may be at play. Our approach resembles Carhart (1997), who shows that a factor based on the momentum effect of Jegadeesh and Titman (1993) almost completely explains the persistence in mutual fund performance

[20] See Banz (1981), Basu (1983), Jegadeesh and Titman (1993), Cooper, Gulen, and Schill (2008), and Novy-Marx (2013), respectively.

[21] The insignificant coefficient on stock return runup reflects the sample period and is not driven by the inclusion of β^{LCT} in the regression.

documented in Hendricks, Patel, and Zeckhauser (1993).

Closely following Fama and French (1993), we use the estimated LCT loadings at the stock level to construct a factor. In particular, at the end of month t, we sort stocks into three groups by LCT loadings (Low L, Medium M, or High H), estimated from Equation (1), and independently into two groups by market capitalizations (Small S or Big B). The assignments are based on breakpoints obtained from NYSE stocks only. We use percentiles 30 and 70 when splitting firms into the three β^{LCT} groups, and the median when splitting them by size. We then compute value-weighted returns of each of the six portfolios in month $t+1$. The resulting leverage constraint tightness risk factor is the average of the two portfolios with low LCT exposure less the average of the high-exposure portfolios, $\text{LCTR} = (\text{LS} + \text{LB})/2 - (\text{HS} + \text{HB})/2$.

Panel A of Table 9 reports moments of the LCTR factor and compares them with those of the commonly considered factors. The mean return on LCTR is 0.29% monthly with a t-statistic of 2.77. Its monthly Sharpe ratio of 0.16 exceeds those of market, size, value, momentum, and liquidity factors. The high Sharpe ratio is primarily driven by a low standard deviation of only 1.84%, much smaller than for any of the other factors (between 3.11% and 4.92%). The higher moments do not suggest that LCTR exhibits unusual tail risks. The skewness is only slightly negative, while the excess kurtosis of 2.69 is larger than that of the market factor, but much smaller than those of size and momentum factors.

Panel B shows that the LCTR factor exhibits low correlations with the others, suggesting that it captures orthogonal information. Further confirming this observation, Panel C indicates that the return on our factor is not explained by others: Alphas from regressions of LCTR on the market, four, and five factors are between 0.31% and 0.33% per month and are statistically significant in all specifications. The LCTR factor does not load on any of the other factors.

We now turn to investigating whether leverage constraint tightness risk helps to explain the differences in returns of β^{LCT}-sorted mutual fund portfolios. Specifically, we add LCTR to the four-factor regressions of mutual fund portfolio returns and evaluate the resulting five-factor alphas. Table 10 summarizes the results. For convenience, the first column repeats four-factor alphas from Tables 4 and 5. The remaining columns show five-factor alphas and the market, size, value, momentum, and LCTR exposures.

The differences in LCTR loadings are pronounced across the decile portfolios. In Panel A, without back-testing, they decline monotonically from 0.33 for the low decile to -0.35 for the high group. The difference, 0.68, is highly significant, and accounting for it explains half, 0.22% out of 0.44% monthly, of the difference in four-factor alphas of the hedge portfolio. In the back-tested sample in Panel B we observe a reduction of similar magnitude. A significant component of the superior performance of the low-β^{LCT} funds is therefore due to high LCTR risk taken on by these funds, and accounting for this risk reduces the degree of outperformance.

The difference in five-factor alphas of the low- and high-exposure portfolios, 0.22% per month, remains important economically. Moreover, after applying the back-testing procedure, the performance differential of 0.44% remains statistically significant (t=2.85). Two possible reasons justify why controlling for LCTR exposure does not entirely explain the differences in returns across β^{LCT}-sorted mutual fund portfolios. First, despite being economically important, the constructed LCTR factor may not capture the true latent factor fully. As a result, loadings on the constructed factor only partially explain differences in decile portfolio returns. Second, the remaining performance differential may be due to managerial skill. However, as the results in Table 6 suggest, the differences in performance across portfolios appear unrelated to previously proposed measures of abilities. Managers of funds with low LCT exposure may instead exhibit a different type of skill related to liquidity management, and hence improve fund performance.

IV. Conclusion

Brunnermeier and Pedersen (2009) suggest that time variation in the tightness of leverage constraints affects the pricing kernel. We propose a theoretically motivated measure for leverage constraint tightness, the market beta of aggregate mutual fund stock holdings. The underlying intuition is that as the desire to take leverage increases, mutual funds, which face significant borrowing restrictions, take advantage of the implicit leverage embedded in high-beta securities. Our measure captures the demand for borrowing and reveals the tightness of leverage constraints, whereas existing proxies are supply-based and focus on the cost or availability of borrowing (e.g., the TED spread). Our LCT proxy correlates with existing measures of funding conditions and forecasts returns of the betting-against-beta factor, in line with the arguments in Frazzini and Pedersen (2014).

Exposure to innovations in LCT strongly predicts mutual fund returns. Funds with low exposure outperform high-exposure funds by more than 5% annually. This finding is robust to adjusting for commonly used risk factors, controlling for fund characteristics, and varying the portfolio formation approaches.

We show in portfolio sorts and Fama and MacBeth (1973) regressions that LCT is also negatively priced in the cross-section of stocks. The negative price of risk is consistent with the theoretical predictions, and reflects the intuition that an asset that pays off when leverage constraints tighten provides capital when it is most valuable. A stock-based leverage constraint tightness risk factor explains approximately half of the mutual fund performance predictability, suggesting that managerial skill also plays an important role.

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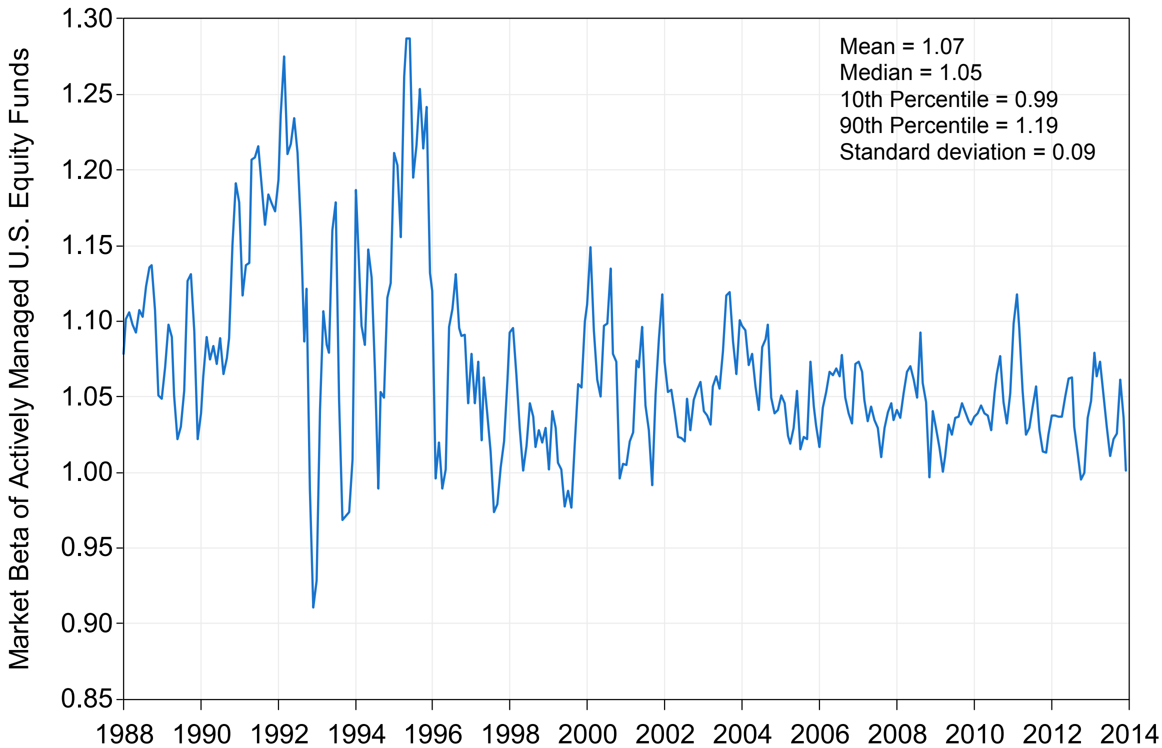

Figure 1. Leverage Constraint Tightness

This figure plots the 3-month moving average of leverage constraint tightness, computed as market beta of the aggregate holdings of all actively managed U.S. equity mutual funds. We calculate the holdings of the aggregate mutual fund in month t as the sum of (i) the holdings of all funds in our sample that disclosed at the end of month $t-1$, (ii) the holdings of funds that disclosed at the end of month $t-2$, adjusted for the stock returns in month $t-1$, and (iii) holdings disclosed in $t-3$, adjusted for the cumulative stock returns in months $t-2$ and $t-1$. For each month t, we then use the daily returns of this aggregate mutual fund portfolio within the month to estimate market beta, using a standard market model regression with one Dimson (1979) lag.

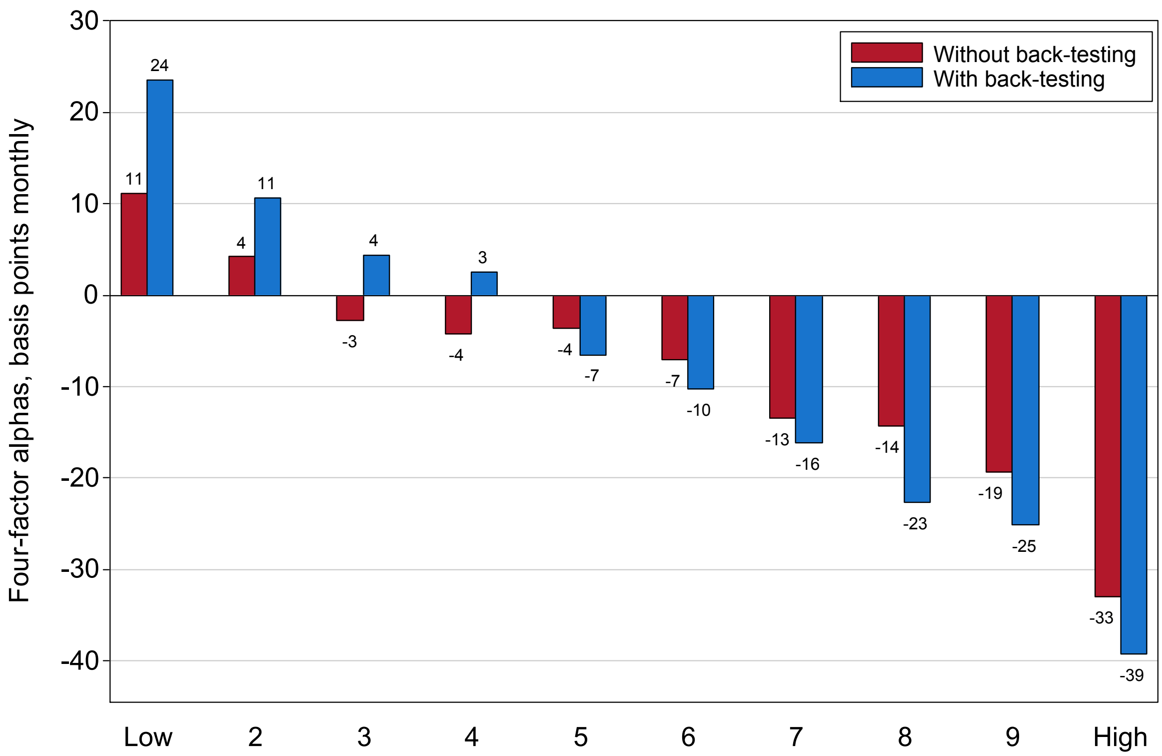

Figure 2. Performance of Leverage Constraint Tightness Portfolios: Mutual Funds This figure plots average four-factor alphas, in basis points per month, for the portfolios of actively managed U.S. equity funds sorted by their loadings on the change in leverage constraint tightness. The left (red) bars show performance measures obtained from the simple sort, and the right (blue) bars from the back-tested strategy. For the simple sort, funds are grouped based on their loadings estimated at the end of month t, and the equal-weighted portfolios are held during month $t + 1$. The back-testing methodology follows Mamaysky, Spiegel, and Zhang (2008): For a fund to be included in a portfolio in month $t + 2$, its cross-sectionally demeaned return in month $t + 1$ has to have the opposite sign of its demeaned loading on the change in leverage constraint tightness computed as of the end of t. The sample period is 1989 to 2013.

Table 1
Correlations of Leverage Constraint Tightness and Proxies of Funding Conditions

This table reports the correlation matrix of quarterly changes of leverage constraint tightness with changes in the Treasury security-based funding liquidity measure, the broker-dealers' leverage factor, as well as AR(1) residuals of broker-dealers' asset growth rate, the TED spread, and the VIX index. We sign all proxies such that positive shocks indicate a worsening of borrowing conditions. Significant correlations are indicated by an asterisk. The sample period is 1988 to 2013.

Variable		(1)	(2)	(3)	(4)	(5)
(1)	Leverage Constraint Tightness					
(2)	$-1\times$Broker-dealer asset growth	0.23*				
(3)	$-1\times$Broker-dealer leverage factor	0.08	0.63*			
(4)	Bond-implied funding liquidity	0.18*	0.21*	0.03		
(5)	TED spread	-0.02	-0.15	-0.35*	0.30*	
(6)	VIX	-0.17*	0.14	-0.12	0.18*	0.29*

Table 2
Leverage Constraint Tightness and BAB Profitability

This table reports in Panel A the coefficients, Newey and West (1987) t-statistics, and adjusted R^2 values from regressions of average monthly betting-against-beta (BAB) factor returns over 1, 6, or 12 months on contemporaneous changes and lagged levels of the leverage constraint tightness measure. Panel B groups the months in the sample into terciles by change or level of leverage constraint tightness and summarizes contemporaneous and future BAB factor returns, shown in percent monthly. The sample period is 1988 to 2013.

A. Regressions	Dependent variable: BAB return over		
	1 month	6 months	12 months
Contemporaneous Δ^{LCT}	-0.034	-0.076	-0.108
t-statistic	[-1.97]	[-2.12]	[-4.56]
Adjusted R^2	0.59	3.65	10.05
Lagged LCT, 1 month	0.027	0.030	0.037
t-statistic	[1.51]	[2.15]	[2.77]
Adjusted R^2	0.05	1.42	3.50
Lagged LCT, 6 months	0.089	0.103	0.124
t-statistic	[2.31]	[3.18]	[4.35]
Adjusted R^2	1.07	6.51	14.74
Lagged LCT, 12 months	0.149	0.171	0.166
t-statistic	[3.26]	[4.04]	[4.64]
Adjusted R^2	2.48	13.50	19.28

B. Sorts	Average monthly BAB return over		
	1 month	6 months	12 months
Contemporaneous Δ^{LCT} *is*			
Low	1.59	1.34	1.66
Medium	0.77	0.52	0.53
High	0.21	0.67	0.34
LCT *during last 1 month is*			
Low	0.72	0.10	-0.20
Medium	0.63	1.17	1.17
High	1.31	1.37	1.67
LCT *during last 6 month is*			
Low	0.72	0.26	-0.12
Medium	0.55	0.88	0.96
High	1.38	1.50	1.79
LCT *during last 12 month is*			
Low	0.77	0.06	-0.01
Medium	0.52	0.92	0.88
High	1.37	1.68	1.78

Table 3
Leverage Constraint Tightness and BAB Profitability: Multivariate Regressions

This table reports the coefficients, Newey and West (1987) t-statistics, and adjusted R^2 values from regressions of the average monthly betting-against-beta (BAB) factor returns over 12 months starting in month t on the following variables measured at the end of $t-1$: 12-month moving average leverage constraint tightness, the negative of the broker-dealer asset growth rate, the negative of the level of broker-dealer leverage calculated by cumulating the factor realizations, bond-implied funding liquidity, the TED spread, and the VIX index. The sample period is 1988 to 2013.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Leverage constraint tightness	0.166							0.197
	[4.64]							[5.07]
$-1\times$ Broker-dealer asset growth		-0.072					-0.049	-0.048
		[-2.22]					[-1.53]	[-1.88]
$-1\times$ Broker-dealer leverage level			0.000				0.000	-0.000
			[0.68]				[1.33]	[-0.76]
Bond-implied funding liquidity				-0.011			-0.003	0.005
				[-2.34]			[-0.69]	[1.09]
TED spread					-0.015		-0.014	-0.019
					[-4.46]		[-2.92]	[-5.02]
VIX						-0.001	-0.000	0.000
						[-2.58]	[-0.21]	[1.44]
Adjusted R^2	19.28	3.95	0.73	5.93	13.22	5.12	18.26	35.22

Table 4
Performance of Leverage Constraint Tightness Portfolios: Mutual Funds

This table reports average excess returns and alphas, in percent per month, and loadings from the five-factor model regressions for the portfolios of actively managed U.S. equity funds sorted by β^{LCT}. β^{LCT} is estimated from rolling regressions of a fund's excess returns on market excess returns and changes in leverage constraint tightness. The bottom row of each panel shows Newey and West (1987) t-statistics for the low-high portfolio. Funds are assigned into groups at the end of every month t, and the equal-weighted portfolios are held during month $t+1$. The five factors are market (MKT), value (HML), size (SMB), momentum (UMD), and Pastor-Stambaugh liquidity (PS). The sample period is 1989 to 2013.

	Excess	Alphas from			5-factor loadings				
Portfolio	return	CAPM	4-factor	5-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{PS}
A. Net-of-expenses returns									
Low	0.76	0.11	0.11	0.10	0.98	0.09	0.16	-0.05	0.01
2	0.69	0.06	0.04	0.04	0.96	0.12	0.11	-0.03	0.01
3	0.63	0.00	-0.03	-0.04	0.96	0.12	0.10	-0.02	0.02
4	0.62	-0.01	-0.04	-0.05	0.97	0.11	0.09	-0.02	0.03
5	0.63	-0.01	-0.04	-0.04	0.97	0.07	0.12	0.00	0.01
6	0.60	-0.04	-0.07	-0.08	0.97	0.05	0.14	0.01	0.02
7	0.55	-0.10	-0.13	-0.14	0.98	0.03	0.18	0.02	0.02
8	0.58	-0.10	-0.14	-0.15	1.00	-0.02	0.28	0.04	0.01
9	0.55	-0.16	-0.19	-0.20	1.02	-0.06	0.37	0.05	0.01
High	0.49	-0.30	-0.33	-0.34	1.11	-0.13	0.52	0.06	0.02
Low-High	0.28	0.41	0.44	0.45	-0.13	0.22	-0.35	-0.11	-0.01
t-stat	[1.86]	[2.37]	[2.97]	[2.98]	[-3.63]	[4.40]	[-7.51]	[-3.56]	[-0.23]
B. Gross-of-expenses returns									
Low-High	0.30	0.41	0.44	0.44	-0.13	0.22	-0.35	-0.11	-0.01
t-stat	[1.89]	[2.36]	[2.97]	[2.97]	[-3.62]	[4.39]	[-7.49]	[-3.56]	[-0.23]
C. Small fund size									
Low-High	0.30	0.46	0.50	0.52	-0.18	0.18	-0.34	-0.11	-0.05
t-stat	[1.94]	[2.60]	[3.19]	[3.31]	[-4.62]	[3.38]	[-6.86]	[-3.31]	[-1.17]
D. Big fund size									
Low-High	0.25	0.36	0.38	0.38	-0.09	0.24	-0.35	-0.11	0.02
t-stat	[1.81]	[2.23]	[2.53]	[2.47]	[-2.32]	[4.55]	[-7.32]	[-3.45]	[0.58]
E. 24-month estimation period									
Low-High	0.27	0.44	0.41	0.40	-0.18	0.27	-0.31	-0.05	0.01
t-stat	[1.47]	[2.55]	[2.67]	[2.62]	[-4.78]	[5.11]	[-6.40]	[-1.62]	[0.31]
F. Using single-factor model									
Low-High	0.53	0.76	0.60	0.60	-0.22	0.29	-0.30	0.09	0.00
t-stat	[2.48]	[3.82]	[3.24]	[3.21]	[-4.89]	[4.57]	[-5.01]	[2.39]	[0.08]
G. Using single-factor model, 24-month estimation period									
Low-High	0.30	0.54	0.44	0.45	-0.26	0.24	-0.32	0.05	-0.03
t-stat	[1.51]	[3.09]	[2.72]	[2.79]	[-6.78]	[4.27]	[-6.29]	[1.59]	[-0.78]

Table 5
Back-tested Performance of Leverage Constraint Tightness Portfolios: Mutual Funds

This table reports average excess returns and alphas, in percent per month, and loadings from the five-factor model regressions for the portfolios of actively managed U.S. equity funds sorted by β^{LCT}. β^{LCT} is estimated from rolling regressions of a fund's excess returns on market excess returns and changes in leverage constraint tightness. The bottom row of each panel shows Newey and West (1987) t-statistics for the low-high portfolio. The back-testing methodology follows Mamaysky, Spiegel, and Zhang (2008): For a fund to be included in a portfolio in month $t+2$, its cross-sectionally demeaned return in month $t+1$ has to be of opposite sign of its demeaned loading on the change in leverage constraint tightness computed as of the end of t. The five factors are market (MKT), value (HML), size (SMB), momentum (UMD), and Pastor-Stambaugh liquidity (PS). The sample period is 1989 to 2013.

	Excess	Alphas from			5-factor loadings				
Portfolio	return	CAPM	4-factor	5-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{PS}
A. Net-of-expenses returns									
Low	0.90	0.27	0.24	0.24	0.93	0.08	0.27	-0.01	0.00
2	0.77	0.14	0.11	0.10	0.96	0.09	0.19	-0.01	0.01
3	0.72	0.09	0.04	0.04	0.97	0.12	0.17	0.00	0.02
4	0.71	0.07	0.03	0.02	0.97	0.07	0.22	0.01	0.01
5	0.62	-0.03	-0.07	-0.07	0.98	0.04	0.21	0.01	0.01
6	0.60	-0.06	-0.10	-0.11	0.99	0.03	0.23	0.02	0.02
7	0.57	-0.11	-0.16	-0.17	1.02	0.00	0.26	0.04	0.02
8	0.52	-0.17	-0.23	-0.23	1.03	-0.04	0.32	0.06	0.01
9	0.51	-0.21	-0.25	-0.26	1.05	-0.07	0.32	0.06	0.02
High	0.38	-0.36	-0.39	-0.41	1.07	-0.12	0.42	0.06	0.03
Low-High	0.51	0.64	0.63	0.64	-0.14	0.20	-0.15	-0.07	-0.03
t-stat	[2.94]	[3.72]	[3.79]	[3.84]	[-3.54]	[3.53]	[-2.81]	[-1.92]	[-0.67]
B. Gross-of-expenses returns									
Low-High	0.51	0.63	0.62	0.64	-0.14	0.20	-0.15	-0.07	-0.03
t-stat	[2.93]	[3.70]	[3.77]	[3.82]	[-3.50]	[3.54]	[-2.79]	[-1.92]	[-0.67]
C. Small fund size									
Low-High	0.47	0.59	0.58	0.59	-0.13	0.20	-0.15	-0.06	-0.03
t-stat	[2.74]	[3.48]	[3.52]	[3.58]	[-3.29]	[3.58]	[-2.81]	[-1.87]	[-0.74]
D. Big fund size									
Low-High	0.51	0.64	0.64	0.65	-0.16	0.20	-0.14	-0.07	-0.02
t-stat	[2.77]	[3.56]	[3.64]	[3.66]	[-3.74]	[3.28]	[-2.50]	[-2.01]	[-0.44]
E. 24-month estimation period									
Low-High	0.65	0.80	0.76	0.74	-0.18	0.17	-0.13	-0.01	0.05
t-stat	[2.50]	[3.10]	[2.89]	[2.78]	[-2.80]	[1.87]	[-1.51]	[-0.13]	[0.73]
F. Using single-factor model									
Low-High	0.69	0.80	0.68	0.69	-0.11	0.25	-0.15	0.05	-0.03
t-stat	[3.10]	[3.67]	[3.16]	[3.19]	[-2.16]	[3.48]	[-2.22]	[1.02]	[-0.47]
G. Using single-factor model, 24-month estimation period									
Low-High	0.58	0.77	0.74	0.75	-0.25	0.22	-0.16	-0.04	-0.04
t-stat	[2.74]	[3.90]	[3.80]	[3.87]	[-5.41]	[3.36]	[-2.65]	[-0.95]	[-0.80]

Table 6
Performance of Leverage Constraint Tightness Portfolios of Mutual Funds Conditional on Measures of Managerial Skill

This table reports the differences in the Carhart (1997) four-factor alphas, in percent per month, of the funds in the low and high decile portfolios sorted by their loadings on the change in leverage constraint tightness. Newey and West (1987) t-statistics are in square brackets. Results are shown conditional on different proxies for managerial skill. At the end of every month t, funds are assigned into halves on the basis of the skill proxies and are next sorted into deciles by loadings on the change in leverage constraint tightness. To obtain the results without back-testing, average equal-weighted returns of each group are then calculated in month $t+1$. The back-testing methodology follows Mamaysky, Spiegel, and Zhang (2008): For a fund to be included in a portfolio in month $t+2$, its cross-sectionally demeaned return in month $t+1$ has to be of opposite sign of its demeaned loading on the change in leverage constraint tightness computed as of the end of t. The sample period is 1989 to 2013, except when using active share, where data availability limits the sample end date to 2011.

	Difference in 4-factor alphas of low- and high-β^{LCT} deciles							
	Without back-testing				With back-testing			
Measure of skill	Low skill		High skill		Low skill		High skill	
Industry concentration	0.22	[2.08]	0.41	[2.41]	0.41	[2.84]	0.54	[2.89]
Return gap	0.32	[2.21]	0.41	[2.53]	0.51	[3.02]	0.55	[3.00]
Active share	0.37	[2.17]	0.46	[2.56]	0.41	[2.70]	0.59	[3.31]
R-squared	0.37	[2.21]	0.31	[2.12]	0.54	[2.96]	0.42	[2.40]
Return runup	0.34	[2.19]	0.37	[2.45]	0.55	[3.59]	0.41	[2.39]
Turnover	0.37	[2.52]	0.42	[2.46]	0.54	[3.11]	0.55	[3.02]

Table 7
Performance of Leverage Constraint Tightness Portfolios: Stocks

This table reports average excess returns and alphas, in percent per month, and loadings from the five-factor model regressions for the portfolios of stocks sorted by β^{LCT}. β^{LCT} is estimated from rolling regressions of a stock's excess returns on market excess returns and changes in leverage constraint tightness. The bottom row of each panel shows Newey and West (1987) t-statistics for the low-high portfolio. Stocks are assigned into groups at the end of every month t, and the value-weighted (Panels A, C, E) and equal-weighted (B, D, F) portfolios are held during month $t+1$. The five factors are market (MKT), value (HML), size (SMB), momentum (UMD), and Pastor-Stambaugh liquidity (PS). The sample period is 1989 to 2013.

	Excess	Alphas from			5-factor loadings				
Portfolio	return	CAPM	4-factor	5-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{PS}
A. Quintiles, value-weighted									
Low	0.94	0.14	0.20	0.24	1.17	-0.04	0.24	-0.08	-0.11
2	0.75	0.14	0.12	0.13	0.98	0.07	-0.11	-0.01	0.00
3	0.81	0.23	0.22	0.23	0.93	0.04	-0.14	0.01	-0.02
4	0.44	-0.20	-0.22	-0.24	1.01	0.06	-0.02	0.00	0.03
High	0.39	-0.43	-0.38	-0.40	1.18	-0.07	0.29	-0.05	0.05
Low-High	0.55	0.57	0.58	0.65	-0.01	0.03	-0.06	-0.02	-0.15
t-stat	[2.53]	[2.58]	[2.54]	[2.87]	[-0.26]	[0.41]	[-0.78]	[-0.53]	[-2.74]
B. Quintiles, equal-weighted									
Low-High	0.56	0.55	0.62	0.64	-0.02	-0.02	0.06	-0.08	-0.05
t-stat	[4.13]	[4.01]	[4.45]	[4.60]	[-0.59]	[-0.37]	[1.43]	[-2.95]	[-1.44]
C. Halves, value-weighted									
Low-High	0.28	0.31	0.30	0.32	-0.02	0.08	-0.09	-0.01	-0.04
t-stat	[2.69]	[2.94]	[2.82]	[2.99]	[-0.64]	[2.30]	[-2.64]	[-0.61]	[-1.60]
D. Halves, equal-weighted									
Low-High	0.34	0.33	0.37	0.38	0.00	-0.02	0.03	-0.05	-0.03
t-stat	[4.26]	[4.07]	[4.50]	[4.67]	[-0.16]	[-0.65]	[1.35]	[-2.72]	[-1.61]
E. Deciles, value-weighted									
Low-High	0.59	0.61	0.60	0.66	-0.01	0.08	-0.10	-0.01	-0.15
t-stat	[2.14]	[2.22]	[2.10]	[2.33]	[-0.15]	[0.84]	[-1.06]	[-0.19]	[-2.06]
F. Deciles, equal-weighted									
Low-High	0.64	0.62	0.70	0.72	-0.02	0.03	0.09	-0.12	-0.04
t-stat	[3.53]	[3.39]	[3.80]	[3.87]	[-0.34]	[0.44]	[1.47]	[-3.14]	[-0.89]

Table 8
Fama-MacBeth Regressions of Monthly Stock Returns

This table reports the results of monthly Fama-MacBeth regressions. Stock returns in month $t+1$ are regressed on loadings on the change in leverage constraint tightness computed as of t, log of market equity as of t, log of the ratio of book equity to market equity, the stock return during the 11-month period ending in $t-1$, the gross profits-to-assets ratio, and the asset growth rate. The timing of measurement of book-to-market ratios, gross profits-to-assets ratios, and asset growth rates follows the convention of Fama and French (1992). Reported are the average coefficients and the corresponding Newey and West (1987) t-statistics. The sample period is 1989 to 2013.

Variable	(1)	(2)	(3)	(4)	(5)
β^{LCT}	-0.24	-0.21	-0.20	-0.20	-0.20
	[-4.30]	[-3.35]	[-3.21]	[-3.37]	[-3.46]
Log market equity		-0.18	-0.19	-0.19	-0.17
		[-2.84]	[-3.16]	[-3.11]	[-2.98]
Log book-to-market ratio		0.18	0.18	0.20	0.16
		[1.66]	[1.72]	[1.90]	[1.50]
Stock return runup			0.09	0.08	0.06
			[0.34]	[0.29]	[0.24]
Gross profits-to-assets				0.37	0.37
				[2.40]	[2.51]
Asset growth					-0.28
					[-4.60]

Table 9
Summary Statistics of Risk Factors

This table reports summary statistics for the leverage constraint tightness risk factor (LCTR) as well as for market, value, size, momentum, and Pastor-Stambaugh liquidity factors. All data are monthly. Means, standard deviations, and alphas are in percent. To construct the LCTR factor, at the end of month t stocks are sorted into three groups by loadings on the change in LCT (Low L, Medium M, or High H) and are independently assigned into two groups on market capitalizations (Small S or Big B). The assignment is based on breakpoints obtained from NYSE stocks (percentiles 30 and 70 for LCT, 50 for size). Value-weighted returns of each of the six portfolios are then computed in month $t+1$. The LCTR factor is $\text{LCTR} = (\text{LS} + \text{LB})/2 - (\text{HS} + \text{HB})/2$. The sample period is 1989 to 2013.

A. Summary Statistics

	LCTR	MKT	HML	SMB	UMD	PS
Mean	0.29	0.65	0.22	0.17	0.63	0.45
t-stat	2.77	2.57	1.23	0.89	2.21	2.01
Std. Dev.	1.84	4.38	3.11	3.27	4.92	3.89
Sharpe	0.16	0.15	0.07	0.05	0.13	0.12
Skew	-0.23	-0.67	0.10	0.85	-1.67	0.50
Kurt	2.69	1.18	3.19	8.61	11.8	2.61

B. Correlations

	LCTR	MKT	HML	SMB	UMD	PS
LCTR	1.00					
MKT	-0.06	1.00				
HML	0.12	-0.25	1.00			
SMB	-0.11	0.24	-0.32	1.00		
UMD	-0.04	-0.24	-0.14	0.04	1.00	
PS	-0.09	0.03	-0.09	-0.02	0.03	1.00

C. Time-Series Regressions of LCTR on Other Factors

Model	α	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{PS}	Adj R^2
CAPM	0.31	-0.03					0.09
	[2.91]	[-1.12]					
Four-factor	0.31	-0.01	0.05	-0.04	-0.01		0.80
	[2.80]	[-0.55]	[1.30]	[-1.18]	[-0.54]		
Five-factor	0.33	-0.01	0.04	-0.04	-0.01	-0.04	1.07
	[2.94]	[-0.53]	[1.17]	[-1.25]	[-0.51]	[-1.35]	

Table 10
Performance of Leverage Constraint Tightness Portfolios Controlling for the LCTR Factor: Mutual Funds

This table reports alphas, in percent per month, and factor loadings from regressions for the portfolios of actively managed U.S. equity funds sorted by β^{LCT}. β^{LCT} is estimated from rolling regressions of a fund's excess returns on market excess returns and changes in leverage constraint tightness. The bottom row of each panel shows Newey and West (1987) t-statistics for the low-high portfolio. For the simple sort (Panel A), funds are grouped based on their loading estimated at the end of month t, and the equal-weighted portfolios are held during month $t+1$. The back-testing methodology (Panel B) follows Mamaysky, Spiegel, and Zhang (2008): For a fund to be included in a portfolio in month $t+2$, its cross-sectionally demeaned return in month $t+1$ has to be of opposite sign of its demeaned loading on the change in leverage constraint tightness computed as of the end of t. The factors are market (MKT), value (HML), size (SMB), momentum (UMD), and leverage constraint tightness (LCTR). The sample period is 1989 to 2013.

	Alphas from		Factor loadings				
Portfolio	4-factor	4+LCTR	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{LCTR}
A. Without back-testing							
Low	0.11	0.00	0.99	0.08	0.18	-0.04	0.33
2	0.04	0.03	0.97	0.12	0.12	-0.03	0.20
3	-0.03	-0.05	0.96	0.11	0.10	-0.02	0.12
4	-0.04	-0.07	0.98	0.11	0.10	-0.01	0.07
5	-0.04	-0.04	0.97	0.06	0.11	0.00	0.02
6	-0.07	-0.08	0.98	0.05	0.14	0.01	-0.01
7	-0.13	-0.10	0.98	0.03	0.17	0.02	-0.09
8	-0.14	-0.10	1.00	-0.01	0.27	0.04	-0.16
9	-0.19	-0.11	1.01	-0.05	0.36	0.05	-0.22
High	-0.33	-0.22	1.10	-0.12	0.50	0.06	-0.35
Low-High	0.44	0.22	-0.12	0.20	-0.32	-0.10	0.68
t-stat	[2.97]	[1.67]	[-3.74]	[4.58]	[-7.97]	[-3.71]	[10.03]
B. With back-testing							
Low	0.24	0.16	0.93	0.07	0.28	0.00	0.26
2	0.11	0.06	0.96	0.09	0.19	-0.01	0.16
3	0.04	-0.03	0.97	0.11	0.17	0.00	0.07
4	0.03	0.02	0.97	0.07	0.22	0.01	0.01
5	-0.07	-0.05	0.98	0.04	0.20	0.01	-0.04
6	-0.10	-0.09	0.99	0.03	0.23	0.02	-0.04
7	-0.16	-0.13	1.02	0.00	0.26	0.04	-0.10
8	-0.23	-0.19	1.02	-0.03	0.31	0.06	-0.13
9	-0.25	-0.20	1.05	-0.07	0.31	0.06	-0.16
High	-0.39	-0.28	1.07	-0.10	0.40	0.06	-0.36
Low-High	0.63	0.44	-0.13	0.17	-0.12	-0.06	0.62
t-stat	[3.79]	[2.85]	[-3.64]	[3.35]	[-2.51]	[-1.88]	[7.77]