When Funding Constraints Bind: Mutual Fund Risk Taking, Performance, and the Cross-Section of Stock Returns

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ABSTRACT

Standard supply-based measures of funding liquidity, such as the cost of borrowing, inadequately capture the unobservable funding constraint tightness (FCT) of investors prohibited from using leverage. Following prior theory, we argue that the observed risk taken by mutual funds, who face stringent leverage restrictions, reveals their FCT. We show that the average market beta of all actively managed equity funds is a demand-based FCT proxy that significantly correlates with existing measures of funding liquidity. Mutual funds' FCT 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 over 5% annually. For stocks, this difference reaches 7%. Our results provide evidence that the tightness of funding constraints has important implications for asset prices.

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Abstract

Standard supply-based measures of funding liquidity, such as the cost of borrowing, inadequately capture the unobservable funding constraint tightness (FCT) of investors prohibited from using leverage. Following prior theory, we argue that the observed risk taken by mutual funds, who face stringent leverage restrictions, reveals their FCT. We show that the average market beta of all actively managed equity funds is a demand-based FCT proxy that significantly correlates with existing measures of funding liquidity. Mutual funds' FCT 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 over 5% annually. For stocks, this difference reaches 7%. Our results provide evidence that the tightness of funding constraints has important implications for asset prices.

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 borrowing 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 high-beta assets (Frazzini and Pedersen, "FP", 2014).[1]

In this paper, we study the impact of funding constraints on financial intermediaries that at first glance seems unaffected by time-varying funding liquidity: mutual funds. The funds face borrowing restrictions established by the Investment Company Act of 1940 and often self-impose stringent zero-leverage constraints.[2] As a result, traditional supply-based proxies of funding liquidity, such as the cost of borrowing or the borrowing capacity, do not directly apply to them.

The borrowing restrictions of mutual funds allow us to extract a demand-based proxy for the funding constraints tightness (FCT), a measure closely resembling the theoretically priced Lagrange multiplier on the funding constraint. In general, for leverage constraints to be binding, investors must have the desire to borrow, but the cost or availability of funding prevents them. Traditional measures focus on the supply-driven cost component, and ignore the demand for borrowing.[3] Since mutual funds face constant borrowing restrictions, a mutual fund-based FCT measure must capture the desire to take on, rather than the cost of, leverage, and we begin our analysis by introducing a new measure of FCT.[4]

[1]In early work, Brennan (1971) and Black (1972) analyze pricing implications of costly or unavailable borrowing in static settings.

[2]For example, Almazan, Brown, Carlson, and Chapman (2004) report that less than 8% of funds engage in any borrowing.

[3]Previously proposed variables can coarsely be categorized into three groups. First, variables that proxy for the cost or availability of funding, such as the TED spread (FP) and the leverage of broker-dealers (Adrian, Etula, and Muir, 2014). Proxies in the second group are based on the arguments following Shleifer and Vishny (1997) and Gromb and Vayanos (2002) that, if arbitrageurs are funding constraint, we should observe more arbitrage violations. The treasury bond funding liquidity measure of Fontaine and Garcia (2012) falls in this category. Lastly, funding liquidity is generally related to uncertainty and risk in the market, measured for example by the VIX. Our measure follows Brunnermeier and Pedersen (2009) and FP, who show that the relevant metric for asset pricing is the Lagrange multiplier associated with the funding constraint. Our FCT measure attempts to most directly capture of the cost of the constraint.

[4]Moreover, 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.

Theory developed in FP and Alankar, Blaustein, and Scholes (2014) suggests that mutual funds shift to riskier assets when funding constraints bind. Inverting their reasoning, we argue that the observable risk taken on by mutual funds should reveal the unobservable tightness of the constraints. To estimate this risk, we calculate the weighted average beta of the holdings of all actively managed equity funds. We show that the average beta fluctuates significantly over time and correlates with existing measures of funding liquidity.

FCT strongly and significantly predicts returns of FP's betting-against-beta factor (BAB), which is long levered low-beta assets and short de-levered high-beta assets, over horizons ranging from one month to one year. Times of binding funding constraints (high average mutual fund betas) are followed by large BAB returns, or high returns of low-beta stocks relative to high-beta stocks. Importantly, this positive relation is consistent with the theoretical prediction in FP, and contrasts with their observation that the TED spread, an alternative proxy for funding constraints, predicts BAB returns with a theoretically incorrect negative sign. FCT alone explains 19% of the variation in future annual BAB returns. The economic magnitude of this predictability is very large: Following times of high FCT, the BAB portfolio generates average returns of 1.70% per month, while it earns negative returns after low-FCT periods. Other funding liquidity proxies fail to robustly predict BAB returns and yield lower R^2.

Having established that the aggregate mutual fund beta is a theoretically and empirically compelling proxy for FCT, we turn to the pricing implications. Our first set of tests analyzes future performance of funds with different exposure to changes in FCT. For each fund, we run rolling regressions of its excess returns on market excess returns and changes in FCT. We assign funds cross-sectionally into groups on the basis of the estimated FCT loadings and evaluate future returns of the groups. The results show that funds' exposure to changes in FCT strongly and negatively predicts fund performance. The magnitude of the effect is economically large: Over the period from 1988 to 2013, the decile of funds with the lowest exposure outperforms the one with the highest exposure by 0.44% per month. The effect is not confined to extreme deciles; rather, fund returns decrease monotonically with FCT exposure.

The negative relation between FCT loadings and future fund performance cannot be explained by standard risk adjustment, remains 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 and holding periods. The difference in future returns of low- and high-exposure funds reaches a striking 0.64% monthly in response to variations in portfolio formation methodology. Consistent with the idea that existing proxies of funding liquidity are not directly applicable to mutual funds, we also show that funds' exposures to these proxies is unrelated to performance.

What drives the inverse relation between FCT exposures and future mutual fund returns? We hypothesize that it is due to the existence of a priced factor relating to funding constraint tightness, as suggested in Brunnermeier and Pedersen (2009). If binding constraints are perceived negatively, an asset that pays off when constraints tighten provides a hedge and should carry a negative risk premium. If that is the case empirically, strong relative performance of funds with low-FCT exposures may be viewed as compensation for funding constraint tightness risk.

We begin the investigation of the risk-based explanation of mutual fund return predictability by asking whether loadings on changes in FCT forecast returns at the firm level. Following the same approach used with mutual funds, we run rolling stock-level regressions to obtain FCT loadings. We find that the estimated FCT 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 and to variations in portfolio formation and weighting methodology.

Fama and MacBeth (1973) regressions confirm that exposure to innovations in FCT strongly and robustly predicts future returns. The average coefficient on FCT loadings is significant in all specification, even after controlling for a number of characteristics known to forecast stock returns. Economically, a one-standard-deviation increase in FCT exposure results in a 0.18% reduction in future monthly returns.

Following the procedure in Fama and French (1993), we construct a funding constraint tightness risk factor based on the cross-sectional exposure to FCT. 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, and momentum factors. We show that controlling for loadings on the funding constraint tightness risk factor attenuates the spread in returns of FCT exposure-sorted mutual fund portfolios. A significant component of the superior performance of the low-exposure funds is thus inherited from stocks with high funding constraint tightness risk. The remaining component of the return spread retains economic and statistical significance, suggesting that another force, such as mutual fund specific risk or differences in managerial skills across mutual fund portfolios, contributes to the differences in performance.

Literature

Our central contribution is to the literature studying the effects of funding constraints on asset prices. The early literature 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 funding constraints that vary across investors and over time. In their model, when explicit leverage is constrained, investors substitute the higher implicit leverage embedded in high-beta assets, bidding up their prices. Our FCT proxy helps to reconcile their theory with empirical findings.

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 liquidity can enter the pricing kernel. In their model, the Lagrange multiplier on the funding constraint places a higher value on states in which funding constraints are tighter. This establishes funding liquidity as a risk factor, and covariation with this factor is negatively priced.

These ideas are tested in Fontaine, Garcia, and Gungor (2014) using a funding liquidity proxy derived from arbitrage violations in U.S. Treasury bonds (Fontaine and Garcia, 2012). They find that their factor 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 assets, and does not rely on an tight link to market liquidity.

Chen and Lu (2013) refine the BAB factor by separating out stocks that are a priori more exposed to funding liquidity. They show that exposure to their funding liquidity proxy is related to hedge fund performance, but argue that it proxies for managerial ability to time funding liquidity, rather than for a risk factor. Finding effects of funding liquidity in hedge funds is somewhat less surprising since hedge funds actively utilize leverage (Ang, Gorovyy, and van Inwegen, 2011). Our measure for the revealed tightness of funding constraints suggests that funding liquidity concerns are also of high importance even for more conservative investors that do not engage 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. As a result, it is empirically difficult to distinguish this test of an intermediary-based theory from more general funding liquidity explanations. We measure the unobservable tightness of funding constraints, which for mutual funds can be binding even if borrowing was available. In contrast to the broker-dealer leverage, our FCT measure has a clean interpretation related to funding constraints, and is priced in the cross-section of mutual funds and individual stocks.

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), and Buffa, Vayanos, and Woolley (2014) show that the simple and often implemented monitoring strategy, inspecting tracking errors, leads delegated asset managers to increase the market risk of their investments.[5] Alankar, Blaustein, and Scholes (2014) generalize Roll (1992) by adding a liquidity constraint in form of a minimum cash level. The minimum cash level implies that, even if the benchmark portfolios are efficient, the tracking error portfolios are not. In their model, similar to FP, managers buy higher volatility stocks than in the benchmark to undo their liquidity constrained and 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 liquidity 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). More closely 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 funding constraint tightness is an important determinant of the cross-section of mutual fund performance.

I. Funding Constraints Tightness

We introduce a theoretically motivated measure of funding constraint tightness. We show empirically that our measure of FCT co-moves with proxies suggested in previous literature, and robustly predicts returns of the BAB factor at horizons from one month to one year. Our FCT measure also captures information unique to mutual funds, in particular related to their cash holdings.

[5] "Tracking error constraints" refers to the objective to minimize the variance of deviations from a benchmark portfolio while beating the benchmark in expected returns.

A. Measuring Funding Constraint Tightness

The theoretical arguments of FP and Alankar, Blaustein, and Scholes (2014) suggest that investment companies compensate for their inability to increase explicit leverage in times of binding funding constraints by shifting their portfolio to riskier securities, thus utilizing the leverage embedded in high-beta securities. Reversing the theoretical argument suggests that the observable risk taken by mutual funds can capture unobservable FCT. Motivated by this logic, we proxy for FCT by the market beta of the holdings of the aggregate mutual fund.

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. As in Amihud and Goyenko (2013), we delete funds with names missing in CRSP and address Evans (2010) incubation bias by eliminating observations preceding the fund's starting year as reported in CRSP. In the resulting 1988-2013 sample, we combine multiple share classes into a single fund.

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.[6] 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

[6]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. Out of funds in our sample that disclosed their holdings at least once in the preceding 12 months, 80% did so in the preceding quarter.

funds that disclosed at the end of month $t-2$, adjusted for the stock return in month $t-1$, and (iii) holdings disclosed in $t-3$, adjusted for the cumulative stock return 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 focus on risk estimated from returns of mutual fund holdings of risky assets rather than from the total fund returns. The difference between the two measures is largely explained by 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. Practical reasons also guide our choice. We require daily returns to be able to estimate FCT at a relatively high monthly frequency, and daily mutual fund returns are not available before September 1998. Using fund-level returns would thus significantly shorten our sample. Further, data on cash holdings are disclosed infrequently, and so using this data to infer daily holdings-level returns from fund-level returns would require additional assumptions. Nonetheless, in untabulated analysis we reaffirm our main results with an FCT measure obtained from fund returns.

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 meaningful 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 seems to be decreasing over time. This is consistent with the growth of the mutual fund industry, as aggregate mutual fund holdings make up a growing component of the market portfolio. Importantly, the decrease in volatility does not affect our key tests because they are conditional in nature and use a rolling window of observations.[7]

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

B. Aggregate Mutual Fund Beta and Funding Liquidity

While the theoretical link between aggregate mutual fund beta and funding constraint tightness is well-motivated, it is less clear that there is a robust empirical relation. Beta can change for reasons other than funding constraint tightness. For example, as a response to managers' changing expectations about the relative performance of high versus low beta assets. Alternatively, if beta was just not an important consideration in the portfolio formation process, it would fluctuate passively due to changing stock weights and randomly with portfolio turnover. We show that our FCT measure correlates with five funding liquidity proxies that have been proposed in the literature.

Adrian and Shin (2010) suggest that the asset growth of broker-dealers increases 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 their 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 as a funding illiquidity measure (e.g., Gârleanu and Pedersen, 2011, FP) as it relates to the borrowing cost. Lastly, episodes of limited funding liquidity are empirically strongly related to aggregate uncertainty, as proxied by the VIX (Ang, Gorovyy, and van Inwegen, 2011).

We are interested in how shocks to funding liquidity proxies from the prior literature relate to our FCT measure. Since both broker-dealer asset growth and leverage are only available at a quarterly frequency, we only use the last observation in each quarter for the monthly variables. Shocks to our measure are the changes in FCT 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 such that positive shocks indicate tightening of funding conditions

Table 1 shows the pairwise correlations between funding liquidity shocks. Our measure is significantly positively correlated with (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 insignificant (0.08). These three measures suggest that high levels of our FCT proxy are associated with low levels of funding liquidity. FCT does not correlate with the TED spread. This is not surprising, since the TED spread measures the cost of borrowing, an aspect of funding liquidity not directly applicable to mutual funds.

The 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 funding 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 demand for borrowing. The negative correlation with VIX is therefore consistent with our demand driven measure of FCT. Overall, the evidence suggests that the aggregate mutual fund beta is a compelling measure for funding constraint tightness.

Funding constraint tightness captures not only information contained in other measures of funding liquidity, but also information unique to mutual funds. Table 2 shows in specification (1) results of the time-series regression of changes in FCT on lagged changes in the cash allocations of actively managed equity funds, obtained from Morningstar. An increase in cash positions can be expected to alleviate the tightness of the funding constraints, and regressions results indicate that this is indeed the case.[9] Change in cash negatively and significantly relates to subsequent change in FCT, explaining 12.6% in its time-series variation. Regression (2) shows that FCT also reacts to lagged market return. Following strong market performance, the weight of high-beta stocks in mutual fund portfolios increases. Subsequently, mutual funds actively de-lever, leading to a

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

[9] In contrast, if a major incentive of funds was to keep overall fund risk constant, an increase in cash (decrease in leverage) should be associated with higher beta of the risky portfolio.

decline in FCT.

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

The relation between FCT and BAB warrants a more detailed discussion. The model of FP predicts that when funding constraints become more binding, 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, which they use as a proxy for the tightness of funding constraints, are negatively related to the contemporaneous BAB return. But, contrasting the second prediction, the level of the TED spread predicts BAB negatively. We now test these predictions using our FCT measure.

We show in Table 3 that when FCT is used to proxy for funding liquidity, the empirical evidence supports the theoretical predictions in FP. Panel A presents regressions where the dependent variable is the BAB return over one, six, and 12 months, expressed in percent monthly. The explanatory variables are contemporaneous changes in FCT as well as its lagged monthly level. We also consider the 6 and 12 months moving averages of FCT to reduce estimation noise. The contemporaneous change in FCT is negatively related to the BAB return.[10]

Consistent with the second prediction of FP, the monthly level of our FCT proxy is positively related to future BAB returns. The adjusted R^2s in these regressions are low, reaching only 3.5% at a 12-months horizon. However, when we use moving averages to smooth the FCT estimates, all coefficients increase and are significantly positive. The model fits also considerably improve: The R^2 rises to almost 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

[10]While this is consistent with the theoretical predictions, caution is warranted in the interpretation. The change in the risk of a buy-and-hold portfolio is mechanically linked to the contemporaneous difference in returns of low- and high-beta stocks. If low-beta stocks have high returns (a high BAB realization), the weight of low-beta stocks increases in a passive portfolio, leading to a decline in portfolio risk.

variables. The return of the BAB factor in the tercile of months with the the lowest changes (i.e., with the biggest declines) in FCT is 1.59%, while it is only 0.21% when FCT increases the most. Following times of nonbinding constraints (low FCT), the future one-month BAB returns is 0.72%, while it is nearly double that, at 1.31%, in environments with tight funding constraints. Longer-horizon BAB returns relate even stronger to lagged FCT. For example, average BAB return over a year following months with low FCT is negative at -0.20% monthly, while it is 1.67% after high-FCT periods. These results are robust irrespective of whether we use the one month FCT or the smoothed 6- and 12-month measures. The difference in BAB returns following high-tercile versus low-tercile FCT realizations is around 0.6% at the one month horizon and 1.8% monthly at an annual horizon.

In Table 4, we compare the predictive ability of FCT to that of other funding liquidity measures. For predictability, the level of funding liquidity rather than funding liquidity shocks is relevant. Out of all funding liquidity proxies considered, FCT results in the highest univariate R^2 and remains a significant and powerful predictor in multivariate regressions. Moreover, all other variables are either insignificant, or enter with a wrong negative sign.

The strong predictability of BAB provides empirical support to the theoretical predictions of FP and confirms the validity of our FCT proxy. It is also important because BAB is related to estimates of the price of risk from cross-sectional Fama and MacBeth (1973) regressions. Being able to determine factors that affect inference drawn from these tests allows for cleaner identification. Of course, BAB predictability should also be of high interest to the investment community, where the number of vehicles explicitly focusing on low-risk investing has experienced tremendous recent growth.

D. Determinants of the Demand for Borrowing

We have shown that the beta of aggregate mutual fund holdings is related to measures of funding liquidity, and in particular captures the demand for borrowing. Why does this demand change over time? Most importantly, if managers are skilled markettimers, they should increase risk in expectation of high future market returns. If risk management is an important consideration, managers should aim for low exposure in times of high market volatility.

In untabulated results, we show that the aggregate mutual fund beta is insignificantly related to short- and long-run market returns. It does negatively predict market volatility in univariate regressions, but not after controlling for lagged market volatility. This is consistent with the consensus in the mutual fund literature that managers possess limited if any timing skills (e.g., Henriksson, 1984, Daniel, Grinblatt, Titman, and Wermers, 1997).[11]

Importantly, the theoretical asset pricing implications qualitatively depend on the interpretation of the average beta. In an ICAPM 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, as shown for example in Ang, Hodrick, Xing, and Zhang (2006). On the other hand, if beta increases in response to changes in funding constraint tightness, the price of this FCT risk should be negative. The empirical findings in this paper of a negative price of FCT risk do not align with the former explanation, but strongly support the funding liquidity interpretation.

II. Funding Liquidity and Mutual Fund Performance

In this section, we show that funding constraints are priced in the cross-section of mutual funds. We first obtain FCT loadings for each mutual fund from rolling time-series regressions of fund excess returns on market excess returns and changes in the FCT factor. Next, we sort funds into portfolios to show that FCT risk loadings forecast

[11]Ferson and Warther (1996) argue that market-timing estimates for mutual funds are obscured by cash inflows from market-timing investors if frictions prevent the immediate investment of the new capital. Mutual fund managers attempts to increase risk in expectation of high market returns is offset by an increase in cash holdings. This argument does not apply to our measure, which is based on holdings of risky assets only. In fact, Table 2 suggests that mutual fund managers lower their holdings risk in response to inflows.

mutual fund returns. Our main finding is that future fund performance is strongly and negatively predicted by exposure to innovations in funding constraint tightness, suggesting a risk factor associated with funding constraint tightness as in Brunnermeier and Pedersen (2009). The economic magnitude of the predictability is very large, about 5% annually, and remains robust after controlling for existing predictors of fund performance and measures of managerial skill. By contrast, loadings on other funding liquidity proxies do not predict fund returns.

A. Mutual Fund Performance

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

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

where $R^e_{i,\tau}$ and $R^e_{M,\tau}$ are excess returns of fund i and the market in month τ, respectively, and $\Delta^{\text{FCT}}_{\tau} = \text{FCT}_{\tau} - \text{FCT}_{\tau-1}$ is the change in funding constraint tightness. The regression estimates for month t are based on data from $t-11$ to t. To obtain meaningful risk loadings, we require each fund to have non-missing returns in all of the 12 months of the estimation period.

At the end of each month t, we rank funds into deciles by loadings on funding constraint tightness, β^{FCT}_t, and compute the return of each group in month $t+1$ as the equal-weighted average of the fund returns. For completeness, we calculate simple excess returns as well as alphas from the market, Fama and French (1993) three-factor, and Carhart (1997) four-factor models.

Panel A of Table 5 summarizes the net-of-expenses performance measures for decile portfolios and also shows the difference in performance of high- and low-β^{FCT} funds. Irrespective of whether we consider raw or risk-adjusted returns, we find that future fund performance declines monotonically with FCT loadings. The magnitude of the effect is economically large. For example, the decile of funds with the lowest FCT exposure generates monthly excess returns of 0.76%, while the highest decile earns just 0.49%.

The performance differential only amplifies after adjusting for differences in risk across portfolios. In particular, the low-β^{FCT} 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.[12] Most studies of mutual fund performance predictability document considerably smaller return differentials.[13]

The last four columns of Table 5 show unconditional factor loadings of funds in the β^{FCT} groups. While the low-high portfolio loads positively on the value factor, it has negative exposures to market, size, and momentum factors, justifying why risk-adjusted returns of the portfolio exceed its raw returns.

Investors are primarily concerned with fund performance net of expenses, but examining performance before deducting expenses makes it possible to better assess differences in managerial abilities if skilled managers extract rents by charging higher expenses (Berk and Green, 2004). In Panel B of Table 5 we therefore examine the relation between β^{FCT} loadings and future gross-of-fees performance. For brevity, we report only the difference in performance of low and high decile portfolios. The results highlight that the differences in future gross-of-expenses returns of the two groups are as strong or stronger as they are after deducting expenses. For example, the difference in four-factor alphas is 0.46% ($t = 2.92$), or two basis points greater gross of fees than it is net of fees.

To study whether the negative relation between β^{FCT} 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^{FCT} deciles within each group. Panels C and D of Table 5

[12] 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.

[13] 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).

show the returns of the low-high portfolio for small and big funds. The difference in returns of low- and high-β^{FCT} funds is strong among funds with above- and below-median fund size, confirming the robust nature of the β^{FCT}-return relation. For example, the difference in four-factor alphas of funds with low and high FCT betas is 0.50% monthly for small funds and smaller but still statistically and economically significant for large funds (0.37%).

In Panel E, we extend the rolling window used to calculate FCT loadings to 24 months. Doing so reduces estimation noise but comes at the expense of a yielding a 'stale' estimate as short-term fluctuations in FCT loadings average out over longer horizons. Our results remain strong after this adjustment in the methodology.

Lastly, in Panel F we calculate loadings from single-factor regressions that omit the market factor. This approach increases the degrees of freedom and is consistent with the approach used, for example, by Adrian, Etula, and Muir (2014). The results from this estimation are even more striking. The spread in simple returns of the low- and high-β^{FCT} portfolios reaches 0.53% monthly and grows to as much as 0.76% after risk-adjustment. Extending the estimation window to 24 months in Panel G provides similarly strong results. Overall, the results summarized in Table 5 paint a striking picture of a strong inverse relation between funds' exposures to changes in funding constraint tightness and future fund performance.

B. Estimation Error and Backtesting

The risk loadings obtained from regression (1) can suffer from potentially significant estimation errors. As a result, the top and bottom β^{FCT} deciles might be populated by not just the funds with the highest and lowest FTC loadings, but also by funds with the highest estimation error. One way to reduce the error is to use longer windows in the estimation, but it comes with the disadvantage that short-term fluctuations in FCT loadings average out over longer horizons. This is particularly relevant for mutual funds, since on average funds turn over their entire portfolio about once every year (Kacperczyk, Sialm, and Zheng, 2005).

We alleviate the problem of estimation error by using a simple backtesting strategy proposed by Mamaysky, Spiegel, and Zhang (2008). They require the statistical sorting variable, in our case β^{FCT}, 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 backtesting strategy following Kacperczyk, Sialm, and Zheng (2008), Dong and Massa (2013) and Dong, Feng, and Sadka (2014), and eliminate funds for which the cross-sectionally demeaned estimated FTC loading and the demeaned return in the following month have the same sign.

In particular, we first rank funds based on β^{FCT} at the end of month t, just as in the sorting procedure underlying the results in Table 5. But instead of starting to hold 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 funding liquidity exposure should be negatively related to future returns. For funds with above-average funding liquidity betas, we therefore expect below-average returns. If instead we observe above-average returns, there is an increased chance that the funding liquidity beta was affected by estimation error. Consequently, we only keep funds whose demeaned estimated FTC loading and the demeaned return in excess of the market have opposite signs, and hold the portfolio in month $t+2$.

Table 6 summarizes the results of the backtesting strategy. Just as in Table 5, funding liquidity exposure is negatively related to future returns, and risk adjustment using the standard risk factors magnifies this effect. However, the back testing procedure results in a significantly wider spread in the future returns of the β^{FCT}-sorted portfolios. Panel A shows that the spread expands by between 19 and 23 basis points monthly relative to the case without backtesting. 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 alphas between 0.57% and 0.64% 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 6 mirror those in Table 5, highlighting the robust nature of the negative relation between FCT betas and future fund performance.

Figure 2 presents the main results of Tables 5 and 6 graphically. It plots the four-factor alphas of the FTC-exposure-sorted deciles. The left (red) bar shows performance measures obtained from the simple sort, and the right (blue) bars from the backtested strategy. For both approaches, alpha decreases monotonically with FTC exposure. The backtesting increases the alphas of the first four deciles, and decreases the alphas of the remaining groups. As expected, the effects of backtesting 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 returns of a benchmark portfolio (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 fund loadings on changes in FCT simply proxy for these known measures of skill. Nonetheless, to verify robustness of our results, we now investigate whether the ability of FCT 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^{FCT} deciles within each group. Table 7 summarizes the differences in four-factor alphas of the low- and high-β^{FCT} deciles portfolios for the subsets of funds with above- and below-median measures of skill. We show results before and after applying the backtesting methodology, but to conserve space do not report performance of each decile separately. The results convincingly indicate that irrespective of whether the managers are inferred to be skilled, funds with low exposure to FCT innovations outperform high-exposure funds by a significant margin: between 0.22% and 0.59% monthly. These results show that the predictability of mutual fund performance that we uncover is distinct from the results documented in the previous literature.

D. Other Funding Constraint Proxies and Fund Performance

Existing funding liquidity factors, in particular broker-dealer leverage (Adrian, Etula, and Muir, 2014), Treasury security-based funding liquidity (Fontaine, Garcia, and Gungor, 2014), and BAB (Frazzini, Kabiller, and Pedersen, 2013), have been shown to be priced in the cross-section and time-series of equity returns. To empirically evaluate our argument that they do not describe the funding constraint tightness of mutual funds well, we study whether exposure to these factors predict fund performance.

We follow the same methodology as above (e.g., underlying the results in Table 5) but replace our FCT factor by other funding liquidity proxies. Table 8 shows the difference in future returns of funds with low and high exposures to funding liquidity measures. Consistent with our conjecture, we find that none of the loadings on the existing proxies significantly predict returns in the cross-section of mutual funds.

III. Binding Funding Constraints and Stock Returns

The strong negative link between mutual funds' return sensitivity to changes in the tightness of funding constraints and future performance can have two primary causes. First, if FCT 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 FCT, and the performance documented in the previous section can reflect a dimension of managerial skill.

The goal of this section is to demonstrate that a significant part of mutual fund performance related to FCT exposure is inherited from the stocks they hold. Loadings on funding constraint tightness forecast returns at the firm level. 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.[14]

As in the previous section, we first run rolling time-series regressions to obtain loadings on the FCT factor, but now use individual stocks rather than mutual funds. Next, using both portfolio sorts and Fama and MacBeth (1973) regressions we test whether these risk loadings forecast stock returns. Our main result is that exposure to innovations in funding constraint tightness strongly negatively and robustly predict future returns. This finding is consistent with the negative price of exposure to FCT suggested by our mutual funds analysis in the previous section.

A funding constraint tightness factor based on the cross-sectional exposure to FCT provides a risk-return tradeoff that compares favorably with existing factors. Tying the stock-level evidence to the findings of the previous section, we show that this factor attenuates the spread in returns of β^{FCT}-sorted portfolios of mutual funds.

A. Cross-Sectional Return Predictability

We obtain monthly risk loadings, β^{FCT}, as slope coefficients from rolling time-series regressions of individual security excess returns on market excess returns and changes in FCT using the last 12 monthly observations, as in Equation (1). Consistent with the analysis of mutual funds in the previous section, we require all 12 monthly return observations to admit a stock into the sample.[15] To evaluate the cross-sectional predictive power, we form portfolios based on the estimated risk exposures β^{FCT} and examine returns in the month following the estimation period.

We summarize the results of this portfolio analysis in Table 9. Panel A shows that

[14] Ang, Liu, and Schwarz (2010) also emphasize the use of individual stock return data because of the information contained in the cross-section of betas.

[15] 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.

the value-weighted quintile of stocks with low FCT 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. The next three columns show alphas estimated from the CAPM, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model. These alphas paint a similar picture as do excess returns: Alphas are positive for the low-exposure portfolio, ranging from 0.12% to 0.20% monthly, and are strongly negative for the high-exposure portfolio, between -0.38% and -0.43%. The difference, ranging from 0.55% to 0.58%, is always statistically significant.

The last four columns contain the risk loading from the Carhart (1997) four-factor model. There is some evidence that stocks with higher measurement error, such as those with high market betas and small market capitalizations, are overrepresented in the extreme portfolios. Importantly, for the low-high hedge portfolio, all risk loadings are small and statistically insignificant, suggesting that funding constraint tightness is largely orthogonal to standard risk factors.

In the remaining panels, we evaluate robustness by varying portfolio formation and weighting methodology. We repeat the analysis for the hedge portfolio using equal-weighted returns (Panel B), as well 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, with the strongest results obtained when using equal-weighting.

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, including market capitalization, the ratio of book equity to market equity, past stock returns, asset growth, and gross profitability.[16] We use Fama and MacBeth (1973) regressions to investigate whether any of these characteristics subsumes the predictive ability of β^{FCT}.

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

Table 10 presents the results. Regression (1) confirms the negative predictive power of β^{FCT}. The estimated monthly price of FCT risk is negative at -0.24%. Given that the time-series average of the cross-sectional standard deviation of estimated loadings is 0.74, this coefficient implies that a one standard deviation increase in FCT risk results in a 0.18% decrease in 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^{FCT} by characteristics. In all cases, our coefficient of interest remains significantly negative. The point estimate changes only slightly across the specifications. Overall, the results from the portfolio sorts and Fama-MacBeth regressions provide strong evidence that FCT loadings are an important determinant of the cross-section of stock returns, distinct from other commonly considered return predictors.

B. A Funding Liquidity Factor

Given the evidence that funding constraint tightness is a priced risk in the cross-section of stock returns, we now revisit performance predictability of mutual funds. In particular, we ask if the large return differential attributed to the FCT 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 one-year momentum effect of Jegadeesh and Titman (1993) almost completely explains the persistence in mutual fund performance documented in Hendricks, Patel, and Zeckhauser (1993).

Closely following Fama and French (1993), we use the estimated FCT loadings at the stock level to construct a factor. In particular, the at the end of month t, we sort stocks into three groups by loadings on the change in FCT (Low L, Medium M, or High H), estimated from Equation (1), and independently into two groups on market equity (Small S or Big B). All assignment is based on breakpoints obtained from NYSE stocks only. We use percentiles 30 and 70 when splitting firms into the three β^{FCT} 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 funding constraint tightness risk factor, FCTR, is the average of the two portfolios with low FCT exposure less the average of the high exposure portfolios, FCTR $= (\text{LS} + \text{LB})/2 - (\text{HS} + \text{HB})/2$.

Panel A of Table 11 reports moments of the FCTR factor and compares them with those of the commonly considered factors. The mean return on FCTR is 0.31% monthly with a t-statistic of 2.77. Its monthly Sharpe ratio of 0.16 exceeds those of market, size, value, and momentum. 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 FCTR exhibits high tail risk. The skewness is only slightly negative, while the excess kurtosis of 2.69 is larger than for the market factor, but much smaller than the kurtosis of the size and momentum factors.

Panel B shows that the FCTR factor exhibits low correlations with the others, suggesting that it captures orthogonal information. Further confirming this observation, Panel C indicates that the return on the factor is not explained by returns on the others: Alphas from regressions of FCTR on the market, three, and four factors are between 0.30% and 0.31% per month and are statistically significant in all specifications. The FCTR factor does not load on any of the other factors.

Having identified FCTR as an independently important factor, we turn to investigating whether differences in loadings on it help explain differences in returns of β^{FCT}-sorted mutual fund portfolios. Specifically, we add FCTR to the four-factor regressions of portfolio returns and evaluate the resulting five-factor alphas. Table 12 summarizes the results of this analysis. For convenience, the first column repeats four-factor alphas from Tables 5 and 6 without and with back-testing. The remaining columns show five-factor alphas and loadings on the market, size, value, momentum, and FCTR.

The differences in FCTR 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 low-high portfolio. We observe in Panel B a similar reduction in the low-high portfolio return differential in the back-tested sample. In other words, a significant component of the superior performance of the funds with low β^{FCT} exposure is due to high FCTR risk taken on by these funds. Accounting for this risk dramatically reduces the degree of outperformance.

The difference in five-factor alphas of the low- and high-exposure portfolios, 0.22% per month, still remains important economically. Moreover, after applying the back-testing procedure, the resulting performance differential of 0.44% remains statistically significant ($t = 2.85$). Two possible reasons justify why controlling for differences in FCTR loadings does not entirely explain the differences in returns across β^{FCT}-sorted mutual fund portfolios. First, despite being an economically important factor, the constructed FCTR 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 component of superior performance of low-β^{FCT} funds may be due to managerial skill. However, as the results in Table 7 suggest, the differences in performance across portfolios appear unrelated to previously proposed measures of abilities. Managers may instead exhibit a different type of skill by actively trading in response to and in expectation of changes in FCT, and hence improving fund performance.

IV. Conclusion

While it is commonly accepted that mutual funds face more stringent leverage constraints than many other institutional investors, it is not immediately obvious that the degree to which the funding constraints bind varies over time. After all, mutual funds have significant cash holdings, on average about 4% of net asset value in our sample, and are therefore not close to the frequently self-imposed leverage constraints, let alone the restrictions established by the Investment Company Act of 1940.

We propose a theoretically guided measure for funding constraint tightness, the market beta of aggregate mutual fund holdings. The underlying intuition is that as the desire to take explicit leverage increases, mutual funds take advantage of the implicit leverage embedded in high-beta securities. Our measure captures the demand for borrowing and reveals the tightness of funding constraints, whereas existing proxies often use the cost or availability of borrowing (e.g., the TED spread or the broker-dealer leverage) or the ability to exploit arbitrage opportunities (e.g., the treasure bond funding liquidity factor). Our measure moderately correlates with existing proxies, but also captures elements unique to mutual funds, in particular related to managing cash positions.

Empirically, none of the existing measures is priced in the cross-section of mutual funds. This is not unexpected, as most mutual funds naturally do not attempt to borrow; nor are they typical arbitrageurs. However, our proxy is a risk factor with a large and negative price of risk in the cross-section of mutual funds. This evidence directly supports the theory in Brunnermeier and Pedersen (2009) and Frazzini and Pedersen (2014) that the Lagrange multiplier on the funding constraint affects the stochastic discount factor.

We show that our finding on mutual funds extends to the cross-section of individual stock returns, suggesting that mutual funds are the marginal investors in the stocks they hold. An alternative interpretation is that both mutual funds and stocks react to the same underlying funding liquidity shock. This view is less supported in the data since none of the other liquidity proxies seems to have predictive power for mutual fund performance. A stock-based FCT factor explains between one third and one half of the mutual fund performance differential, which suggests that managerial skill also plays an important role.

References

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

Adrian, Tobias, and Hyun Song Shin, 2010, Liquidity and leverage, *Journal of Financial Intermediation* 19, 418–437.

Alankar, Ashwin, Peter Blaustein, and Myron S. Scholes, 2014, The cost of constraints: Risk management, agency theory and asset prices, Working Paper, Stanford University, Palo Alto, CA.

Almazan, A., K. C. Brown, Murray Carlson, and D. A. Chapman, 2004, Why constrain your mutual fund manager?, *Journal of Financial Economics* 73, 289–321.

Amihud, Yakov, and Ruslan Goyenko, 2013, Mutual fund's R^2 as predictor of performance, *Review of Financial Studies* 26, 667–694.

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

Ang, Andrew, Robert J. Hodrick, Yuhang H. Xing, and Xiaoyan Y. Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Ang, Andrew, Jun Liu, and Krista Schwarz, 2010, Using stocks or portfolios in tests of factor models, Working paper, Columbia University, New York, NY.

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler, 2011, Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly, *Financial Analysts Journal* 67, 40–54.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

Basu, Sanjoy, 1983, The relationship between earnings yield, market value and return for nyse common-stocks - further evidence, *Journal of Financial Economics* 12, 129–156.

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

Black, Fisher, 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 45, 444–455.

Bollen, Nicolas P. B., and Jeffrey A. Busse, 2004, Short-term persistence in mutual fund performance, *Review of Financial Studies* 18, 569–597.

Brennan, Michael J., 1971, Capital market equilibrium with divergent borrowing and lending rates, *Journal of Financial and Quantitative Analysis* 6, 1197–1205.

———, 1993, Agency and asset pricing, Working Paper, UCLA, Los Angeles, CA.

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

Buffa, Andrea M., Dimitri Vayanos, and Paul Woolley, 2014, Asset management contracts and equilibrium prices, Working Paper, London School of Economics, London, U.K.

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

Chen, Zhuo, and Andrea Lu, 2013, A market-based funding liquidity measure, Working Paper, Northwestern University, Evanston, IL.

Cooper, Michael J., Huseyin Gulen, and Michael S. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1651.

Cremers, K. J. Martijn, and Antti Petajisto, 2009, How active is your fund manager? a new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Daniel, Kent, Mark S. Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

Dong, Xi, Shu Feng, and Ronnie Sadka, 2014, Does liquidity beta predict mutual-fund alpha?, Working Paper, Boston College, Boston, MA.

Dong, Xi, and Massimo Massa, 2013, Excess autocorrelation and mutual fund performance, Working Paper, INSEAD, Fontainebleau, France.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A first look at the accuracy of the crsp mutual fund database and a comparison of the crsp and morningstar mutual fund databases, *Journal of Finance* 56, 2415–2430.

Evans, Richard B., 2010, Mutual fund incubation, *Journal of Finance* 65, 1581–1611.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferson, Wayne E., and Vincent A. Warther, 1996, Evaluating fund performance in a dynamic market, *Financial Analysts Journal* 52, 20–28.

Fontaine, Jean-Sébastien, and René Garcia, 2012, Bond liquidity premia, *Review of Financial Studies* 25, 1207–1254.

———, and Sermin Gungor, 2014, Funding liquidity risk and the cross-section of stock returns, Working Paper, Bank of Canada, Ottawa, Canada.

Frazzini, Andrea, David Kabiller, and Lasse H. Pedersen, 2013, Buffet's alpha, Working Paper, New York University, NY.

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

Gârleanu, Nicolae, and Lasse H. Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies* 24, 1980–2022.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361–407.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2014, ... and the cross-section of expected returns, Working Paper, Duke University, Durham, NC.

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

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1993, Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988, *Journal of Finance* 48, 93–130.

Henriksson, Roy D., 1984, Market timing and mutual fund performance - an empirical-investigation, *Journal of Business* 57, 73–96.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers - implications for stock-market efficiency, *Journal of Finance* 48, 65–91.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On the industry concentration of actively managed equity mutual funds, *Journal of Finance* 60, 1983–2011.

———, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194.

Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2008, Estimating the dynamics of mutual fund alphas and betas, *Review of Financial Studies* 21, 233–264.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semidefinite, heteroskedasticity and autocorrelation consistent covariance-matrix, *Econometrica* 55, 703–708.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2014, Do funds make more when they trade more?, Working Paper, University of Chicago, Chicago, Il.

Roll, Richard, 1992, A mean/variance analysis of tracking error, *Journal of Portfolio Management* 18, 1322.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1655–1703.

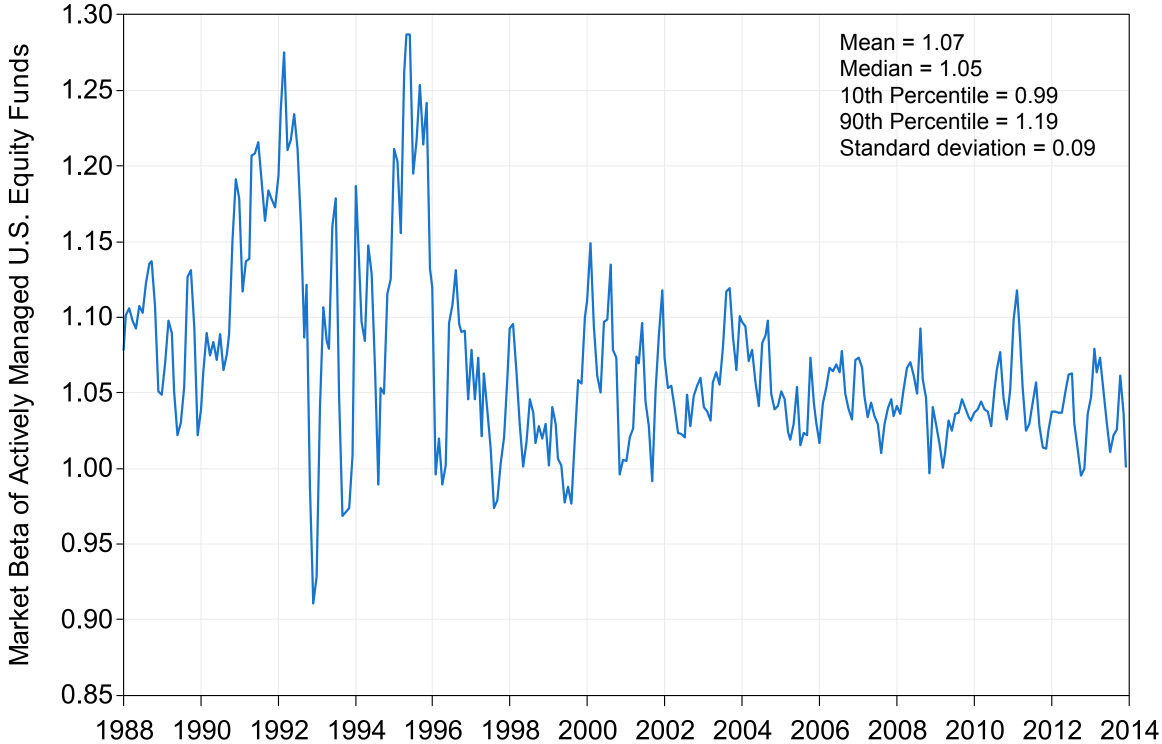

Figure 1. Funding Constraint Tightness

This figure plots the 3-month moving average of funding constraint tightness, computed as market beta of the aggregate holdings of all actively managed U.S. equity mutual funds. In particular, 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 return in month $t-1$, and (iii) holdings disclosed in $t-3$, adjusted for the cumulative stock return 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 a standard market model regression with one Dimson (1979) lag.

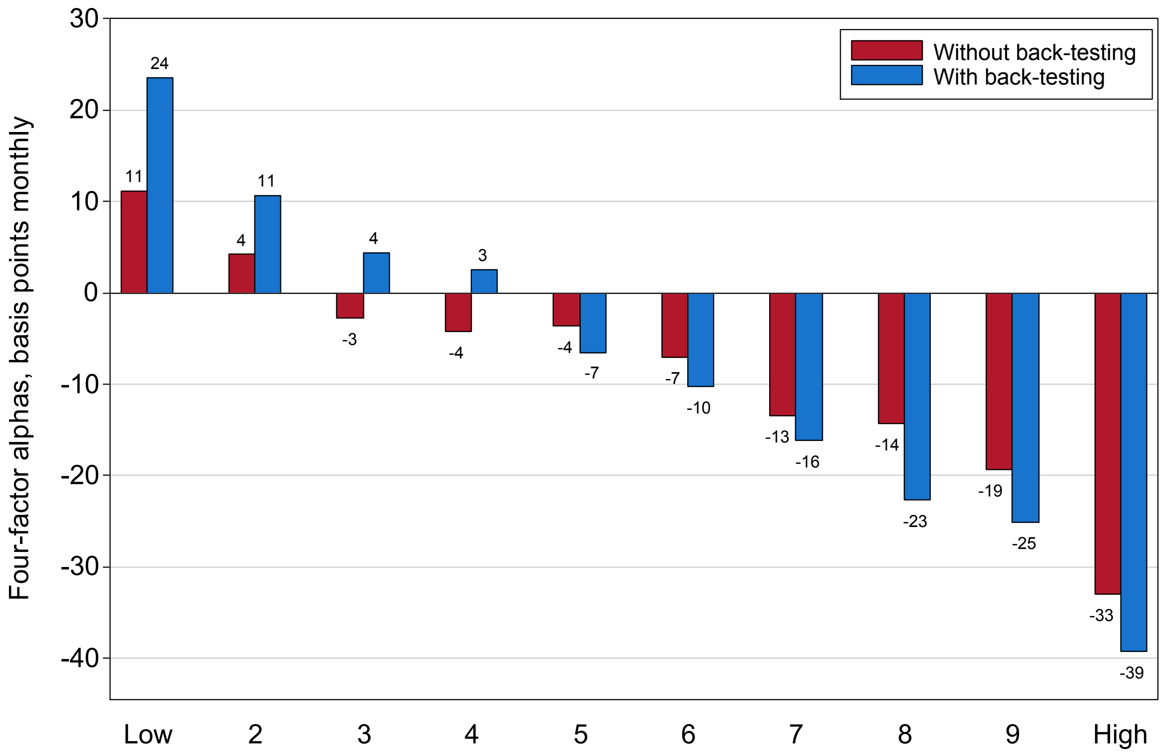

Figure 2. Performance of Funding Constraint Tightness Portfolios: Mutual Funds This figure plots average four-factor alphas, in basis points per month, for the portfolios of actively managed U.S. equity funds sorted by their loadings on the change in funding constraint tightness. The left (red) bar shows performance measures obtained from the simple sort, and the right (blue) bars from the backtested strategy. For the simple sort, 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 backtesting methodology follows Mamaysky, Spiegel, and Zhang (2008): for a fund to be included in a portfolio in month $t+2$, its demeaned return in month $t+1$ has to be of opposite sign of its demeaned loading on the change in funding constraint tightness computed as of the end of t. The sample period is 1989 to 2013.

Table 1
Correlations of Funding Constraint Tightness and Proxies of Funding Liquidity

This table reports the correlation matrix of quarterly changes of funding 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 tightening of funding conditions. Significantly correlations are indicated by an asterisk. The sample period is 1988 to 2013.

	Variable	(1)	(2)	(3)	(4)	(5)
(1)	Funding 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
Market Returns and Mutual Fund Cash Holdings as Determinants of Funding Constraint Tightness

This table reports in the coefficients, Newey and West (1987) t-statistics, and adjusted R^2 values from regressions of changes in funding constraint tightness (Δ^{FCT}) over 12 months on lagged 12-month change in aggregate allocation of actively managed equity funds to cash and market return. The sample period is 1988 to 2013.

	(1)	(2)	(3)
Change in aggregate allocation to cash	-1.22		-1.32
	[-2.78]		[-3.51]
Market return		-0.64	-0.67
		[-2.09]	[-2.99]
Adjusted R^2	12.58	3.25	16.76

Table 3
Funding 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 BAB factor returns over 1, 6, or 12 months on contemporaneous and lagged funding constraint tightness measures. Panel B groups the months in the sample into terciles by the change or level of funding 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^{FCT}	-0.034	-0.076	-0.108
t-statistic	[-1.97]	[-2.12]	[-4.56]
Adjusted R^2	0.59	3.65	10.05
Lagged FCT, 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 FCT, 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 FCT, 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 BAB return over		
	1 month	6 months	12 months
. . . when contemporaneous Δ^{FCT} *is*			
Low	1.59	1.34	1.66
Medium	0.77	0.52	0.53
High	0.21	0.67	0.34
. . . when FCT *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
. . . when FCT *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
. . . when FCT *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 4
Funding 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 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 funding 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)	(9)
Funding constraint tightness	0.166					0.170			0.197
	[4.64]					[6.64]			[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	-0.016		-0.014	-0.019
					[-4.46]	[-4.81]		[-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	33.47	5.12	18.26	35.22

Table 5
Performance of Funding Constraint Tightness Portfolios: Mutual Funds

This table reports average excess returns and alphas, in percent per month, and loadings from the four-factor model regressions for the portfolios of actively managed U.S. equity funds sorted by their loadings on the change in funding 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 four factors are market (MKT), value (HML), size (SMB), and momentum (UMD). The sample period is 1989 to 2013.

	Excess	Alphas from			4-factor loadings			
Portfolio	return	CAPM	3-factor	4-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}
A. Net-of-expenses returns								
Low	0.76	0.11	0.07	0.11	0.98	0.09	0.16	-0.05
2	0.69	0.06	0.01	0.04	0.96	0.12	0.11	-0.03
3	0.63	0.00	-0.04	-0.03	0.96	0.12	0.10	-0.02
4	0.62	-0.01	-0.06	-0.04	0.97	0.11	0.09	-0.02
5	0.63	-0.01	-0.04	-0.04	0.97	0.07	0.12	0.00
6	0.60	-0.04	-0.06	-0.07	0.97	0.05	0.14	0.01
7	0.55	-0.10	-0.12	-0.13	0.98	0.03	0.18	0.02
8	0.58	-0.10	-0.11	-0.14	1.00	-0.02	0.28	0.04
9	0.55	-0.16	-0.15	-0.19	1.02	-0.06	0.37	0.05
High	0.49	-0.30	-0.27	-0.33	1.11	-0.13	0.51	0.06
Low-High	0.28	0.41	0.34	0.44	-0.13	0.22	-0.35	-0.11
t-stat	[1.86]	[2.37]	[2.30]	[2.97]	[-3.64]	[4.45]	[-7.52]	[-3.57]
B. Gross-of-expenses returns								
Low-High	0.30	0.43	0.36	0.46	-0.14	0.21	-0.35	-0.11
t-stat	[1.89]	[2.26]	[2.28]	[2.92]	[-3.67]	[4.05]	[-7.17]	[-3.45]
C. Small fund size								
Low-High	0.30	0.46	0.40	0.50	-0.18	0.19	-0.34	-0.11
t-stat	[1.94]	[2.60]	[2.56]	[3.19]	[-4.64]	[3.50]	[-6.81]	[-3.34]
D. Big fund size								
Low-High	0.25	0.36	0.29	0.38	-0.09	0.23	-0.35	-0.11
t-stat	[1.81]	[2.23]	[2.09]	[2.53]	[-2.35]	[4.52]	[-7.38]	[-3.43]
E. 24-month estimation period								
Low-High	0.27	0.44	0.36	0.41	-0.18	0.27	-0.31	-0.05
t-stat	[1.47]	[2.55]	[2.41]	[2.67]	[-4.78]	[5.11]	[-6.43]	[-1.62]
F. Using single-factor model								
Low-High	0.53	0.76	0.69	0.60	-0.22	0.29	-0.30	0.09
t-stat	[2.48]	[3.82]	[3.73]	[3.24]	[-4.90]	[4.59]	[-5.02]	[2.40]
G. Using single-factor model, 24-month estimation period								
Low-High	0.30	0.54	0.49	0.44	-0.26	0.24	-0.32	0.05
t-stat	[1.51]	[3.09]	[3.06]	[2.72]	[-6.80]	[4.36]	[-6.27]	[1.57]

Table 6
Back-tested Performance of Funding Constraint Tightness Portfolios: Mutual Funds

This table reports average excess returns and alphas, in percent per month, and loadings from the four-factor model regressions for the portfolios of actively managed U.S. equity funds sorted by their loadings on the change in funding 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 backtesting methodology follows Mamaysky, Spiegel, and Zhang (2008): for a fund to be included in a portfolio in month $t+2$, its demeaned return in month $t+1$ has to be of opposite sign of its demeaned loading on the change in funding constraint tightness computed as of the end of t. The four factors are market (MKT), value (HML), size (SMB), and momentum (UMD). The sample period is 1989 to 2013.

	Excess	Alphas from			4-factor loadings			
Portfolio	return	CAPM	3-factor	4-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}
A. Net-of-expenses returns								
Low	0.90	0.27	0.23	0.24	0.93	0.08	0.27	-0.01
2	0.77	0.14	0.09	0.11	0.96	0.09	0.19	-0.01
3	0.72	0.09	0.04	0.04	0.97	0.12	0.17	0.00
4	0.71	0.07	0.04	0.03	0.97	0.07	0.22	0.01
5	0.62	-0.03	-0.05	-0.07	0.98	0.04	0.20	0.01
6	0.60	-0.06	-0.08	-0.10	0.99	0.02	0.23	0.02
7	0.57	-0.11	-0.12	-0.16	1.02	0.00	0.26	0.04
8	0.52	-0.17	-0.17	-0.23	1.03	-0.04	0.32	0.06
9	0.51	-0.21	-0.20	-0.25	1.05	-0.07	0.32	0.06
High	0.38	-0.36	-0.34	-0.39	1.07	-0.12	0.41	0.06
Low-High	0.51	0.64	0.57	0.63	-0.14	0.20	-0.15	-0.07
t-stat	[2.94]	[3.72]	[3.47]	[3.79]	[-3.55]	[3.61]	[-2.78]	[-1.94]
B. Gross-of-expenses returns								
Low-High	0.51	0.63	0.56	0.62	-0.14	0.20	-0.15	-0.07
t-stat	[2.93]	[3.70]	[3.45]	[3.77]	[-3.52]	[3.62]	[-2.76]	[-1.94]
C. Small fund size								
Low-High	0.42	0.53	0.46	0.54	-0.12	0.21	-0.21	-0.09
t-stat	[2.38]	[3.07]	[2.85]	[3.31]	[-3.03]	[3.80]	[-4.05]	[-2.55]
D. Big fund size								
Low-High	0.46	0.58	0.51	0.58	-0.13	0.21	-0.23	-0.07
t-stat	[2.41]	[3.11]	[2.93]	[3.24]	[-3.01]	[3.40]	[-4.04]	[-1.84]
E. 24-month estimation period								
Low-High	0.65	0.80	0.75	0.76	-0.18	0.16	-0.13	-0.01
t-stat	[2.50]	[3.10]	[2.92]	[2.89]	[-2.78]	[1.81]	[-1.55]	[-0.12]
F. Using single-factor model								
Low-High	0.69	0.80	0.72	0.68	-0.11	0.26	-0.15	0.04
t-stat	[3.10]	[3.67]	[3.40]	[3.16]	[-2.18]	[3.54]	[-2.20]	[1.01]
G. Using single-factor model, 24-month estimation period								
Low-High	0.58	0.77	0.70	0.74	-0.25	0.22	-0.16	-0.04
t-stat	[2.74]	[3.90]	[3.69]	[3.80]	[-5.44]	[3.46]	[-2.61]	[-0.97]

Table 7
Performance of Funding Constraint Tightness Portfolios of Mutual Funds Conditional on Measures of Managerial Skill

This table reports the differences in 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 funding constraint tightness. The Newey and West (1987) t-statistics are in square brackets. The 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 funding constraint tightness. To obtain the results without back-testing, average equal-weighted returns of each group are then calculated in month $t+1$. The backtesting methodology follows Mamaysky, Spiegel, and Zhang (2008): for a fund to be included in a portfolio in month $t+2$, its demeaned return in month $t+1$ has to be of opposite sign of its demeaned loading on the change in funding 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^{FCT} 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 8
Loadings on Known Funding Constraint Tightness Proxies and Mutual Funds Performance

This table reports the differences in average excess returns and alphas, in percent per month, of the funds in the low and high decile portfolios sorted by their loadings on different proxies of funding constraint tightness. The proxies include broker-dealer asset growth, broker-dealer leverage factor, change in bond-implied funding liquidity, and the betting-against-beta factor. The Newey and West (1987) t-statistics are in square brackets. Funds are assigned into groups at the end of every month t, and the equal-weighted portfolios are held during month $t+1$. The four factors are market (MKT), value (HML), size (SMB), and momentum (UMD). The sample period is 1989 to 2013.

	Excess	Alphas from			4-factor loadings			
Portfolio	return	CAPM	3-factor	4-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}
A. Broker-dealer asset growth								
Low-High	0.02	0.09	0.21	0.18	-0.10	-0.29	-0.27	0.03
t-stat	[0.16]	[0.66]	[1.63]	[1.38]	[-3.28]	[-6.58]	[-6.57]	[1.18]
B. Broker-dealer leverage factor								
Low-High	-0.08	-0.23	-0.03	-0.05	0.15	-0.52	0.22	0.02
t-stat	[-0.35]	[-1.15]	[-0.22]	[-0.34]	[3.80]	[-9.66]	[4.65]	[0.66]
C. Change in bond-implied funding liquidity								
Low-High	-0.20	-0.21	-0.27	-0.10	0.06	0.16	-0.35	-0.18
t-stat	[-0.98]	[-1.03]	[-1.41]	[-0.54]	[1.38]	[2.57]	[-5.99]	[-4.75]
D. Betting-against-beta factor								
Low-High	0.17	-0.02	0.17	0.04	0.16	-0.59	0.37	0.14
t-stat	[0.70]	[-0.11]	[0.95]	[0.23]	[3.84]	[-9.76]	[6.53]	[3.85]

Table 9
Performance of Funding Constraint Tightness Portfolios: Stocks

This table reports average excess returns and alphas, in percent per month, and loadings from the four-factor model regressions for the portfolios of stocks sorted by their loadings on the change in funding 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 (Panel B, D, F) portfolios are held during month $t+1$. The four factors are market (MKT), value (HML), size (SMB), and momentum (UMD). The sample period is 1989 to 2013.

	Excess	Alphas from			4-factor loadings			
Portfolio	return	CAPM	3-factor	4-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}
A. Quintiles, value-weighted								
Low	0.94	0.14	0.12	0.20	1.17	-0.02	0.25	-0.08
2	0.75	0.14	0.12	0.12	0.98	0.07	-0.11	-0.01
3	0.81	0.23	0.23	0.22	0.93	0.04	-0.14	0.01
4	0.44	-0.20	-0.22	-0.22	1.01	0.06	-0.02	0.00
High	0.39	-0.43	-0.43	-0.38	1.18	-0.07	0.29	-0.05
Low-High	0.55	0.57	0.55	0.58	-0.02	0.05	-0.05	-0.03
t-stat	[2.53]	[2.58]	[2.48]	[2.54]	[-0.30]	[0.65]	[-0.64]	[-0.58]
B. Quintiles, equal-weighted								
Low-High	0.56	0.55	0.54	0.62	-0.02	-0.01	0.07	-0.09
t-stat	[4.13]	[4.01]	[3.91]	[4.45]	[-0.62]	[-0.24]	[1.50]	[-2.97]
C. Halves, value-weighted								
Low-High	0.28	0.31	0.28	0.30	-0.02	0.09	-0.09	-0.01
t-stat	[2.69]	[2.94]	[2.75]	[2.82]	[-0.67]	[2.45]	[-2.56]	[-0.64]
D. Halves, equal-weighted								
Low-High	0.34	0.33	0.33	0.37	0.00	-0.01	0.04	-0.05
t-stat	[4.26]	[4.07]	[4.01]	[4.50]	[-0.19]	[-0.51]	[1.43]	[-2.75]
E. Deciles, value-weighted								
Low-High	0.59	0.61	0.58	0.60	-0.01	0.10	-0.09	-0.01
t-stat	[2.14]	[2.22]	[2.09]	[2.10]	[-0.18]	[1.03]	[-0.95]	[-0.23]
F. Deciles, equal-weighted								
Low-High	0.64	0.62	0.59	0.70	-0.02	0.03	0.09	-0.12
t-stat	[3.53]	[3.39]	[3.21]	[3.80]	[-0.35]	[0.53]	[1.51]	[-3.16]

Table 10
Fama-MacBeth Regressions of Monthly Stock Returns

This table reports the results of monthly Fama-MacBeth regressions. Stock returns in month t are regressed on loadings on the change in funding constraint tightness computed as of $t-1$, log of market equity as of $t-1$, log of the ratio of book equity to market equity, the stock return during the 11-month period ending in $t-2$, 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. Details of variable definitions are in Appendix A. The sample period is 1989 to 2013.

Variable	(1)	(2)	(3)	(4)	(5)
β^{FCT}	-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-asset				0.37	0.37
				[2.40]	[2.51]
Asset growth					-0.28
					[-4.60]

Table 11
Summary Statistics of Risk Factors

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

A. Summary Statistics

	FCTR	MKT	HML	SMB	UMD
Mean	0.29	0.65	0.22	0.17	0.63
t-stat	2.77	2.57	1.23	0.89	2.21
Std. Dev.	1.84	4.38	3.11	3.27	4.92
Sharpe	0.16	0.15	0.07	0.05	0.13
Skew	-0.23	-0.67	0.10	0.85	-1.67
Kurt	2.69	1.18	3.19	8.61	11.8
Min	-7.64	-17.2	-12.7	-16.4	-34.7
Max	7.87	11.3	13.9	22.0	18.4

B. Correlations

	FCTR	MKT	HML	SMB	UMD
FCTR	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

C. Time-Series Regressions of FCTR on Other Factors

Model	α	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	Adj R^2
CAPM	0.31	-0.03				0.09
	[2.91]	[-1.12]				
Three-factor	0.30	-0.01	0.05	-0.04		1.04
	[2.75]	[-0.42]	[1.44]	[-1.21]		
Four-factor	0.31	-0.01	0.05	-0.04	-0.01	0.80
	[2.80]	[-0.55]	[1.30]	[-1.18]	[-0.54]	

Table 12
Performance of Funding Constraint Tightness Portfolios Controlling for the FCTR Factor: Mutual Funds

This table reports 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 their loadings on the change in funding 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 backtesting methodology (Panel B) follows Mamaysky, Spiegel, and Zhang (2008): for a fund to be included in a portfolio in month $t+2$, its demeaned return in month $t+1$ has to be of opposite sign of its demeaned loading on the change in funding constraint tightness computed as of the end of t. The five factors are market (MKT), value (HML), size (SMB), and momentum (UMD), and funding constraint tightness (FCTR). The sample period is 1989 to 2013.

	4-factor	5-factor	5-factor loadings				
Portfolio	alpha	alpha	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{FCTR}
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]