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Leverage constraints and asset prices: Insights from mutual fund risk taking☆

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ABSTRACT

Prior theory suggests that time variation in the degree to which leverage constraints bind affects the pricing kernel. We propose a 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 desire for leverage and thus the tightness of 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 5% annually, and for stocks this difference reaches 7%. Our results show that the tightness of leverage constraints has important implications for asset prices.

1. Introduction

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 (Black, 1972; Frazzini and Pedersen, "FP," 2014).

Leverage constraints bind when more leverage is desired than available. We propose a measure for the "tightness" of leverage constraints—the analogue to the theoretically priced Lagrange multiplier—derived from financial intermediaries for whom leverage is generally not available: actively managed equity mutual funds. These investors face leverage restrictions established by the Investment Company Act of 1940 and often self-impose

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stringent zero-leverage constraints.[1] While mutual funds may be prohibited from using explicit leverage, they can take on leverage implicit in high-beta stocks.

Building on Black (1972) and FP, we show theoretically that mutual funds shift to riskier assets when leverage constraints bind. Inverting this reasoning, we argue that the observable risk taken on by mutual funds reveals their desire for leverage and hence the unobservable tightness of the constraint. Since mutual funds are not directly affected by funding conditions, our measure is distinct from and complementary to proxies capturing the cost or availability of borrowing.[2]

To recognize the positive link between the level of mutual fund beta and the tightness of leverage constraints, consider a manager who wants to achieve a fund beta of 1.1. The manager can do this by simply buying stocks with this desired beta. Another alternative, available only to an unconstrained manager, is to borrow 10% of the capital and invest everything in the market portfolio. As long as the market return in excess of the borrowing cost is larger than the cross-sectional reward for taking on an additional unit of beta risk, as is consistent with empirical evidence (e.g., Black, Jensen, and Scholes, 1972), the manager will always prefer the second alternative of levering the market portfolio. Only constrained managers who are unable to borrow would invest in high-beta stocks. The higher the beta the manager wants to achieve, the more costly the leverage constraint becomes, i.e., the greater the degree to which it binds. Aggregate beta thus reveals the aggregate tightness of leverage constraints. Note that we are agnostic whether the demand for higher beta is due to attempts to time the market, agency reasons, changing preferences, or other causes. The relation between the level of beta and the degree to which leverage constraints bind materializes irrespective of the cause.

We calculate the value-weighted average beta of the aggregate stock holdings of all actively managed equity funds and show that this measure of leverage constraint tightness (LCT) correlates with existing proxies of funding conditions. Further, it strongly and significantly predicts returns of FP's betting-against-beta (BAB) factor, which consists of a long position in levered low-beta stocks and a short position in de-levered high-beta stocks.[3] Times of binding leverage constraints are followed by high BAB returns. Importantly, this positive relation is consistent with the prediction in FP, and contrasts with their empirical observation that the TED spread, a proxy for the cost of borrowing, predicts BAB returns with a theoretically incorrect negative sign. LCT alone explains 16% 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 1.30% per month, while it earns only half a percent 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, we run rolling regressions of excess returns of each fund on market excess returns and innovations in LCT, defined as residuals from an $AR(1)$ model. We show that exposure to LCT innovations strongly and inversely predicts fund performance in the cross-section. The magnitude of the effect is economically large: During the period from 1981 to 2014, the decile of funds with the lowest exposure outperforms the one with the highest exposure by 0.41% per month after controlling for standard factors. The effect is not confined to extreme deciles; rather, fund returns decrease steadily with LCT exposure.

The negative relation between LCT loadings and future fund performance remains large in gross-of-fees returns, and is robust to controlling for fund characteristics and determinants of mutual fund performance from prior literature, as well as to alternative estimation approaches. The difference in future returns of low- and high-exposure funds exceeds 0.60% monthly in response to variations in portfolio formation methods.

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 low 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.

To assess the risk-based explanation of mutual fund return forecastability, we ask 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 estimated LCT exposures negatively predict stock returns in the cross-section. The difference in performance between quintiles of firms with low and high loadings is 0.54% monthly and is statistically significant. This result is robust to standard factor adjustments, to variations in portfolio formation and weighting schemes, and to controlling

[1] For example, Almazan, Brown, Carlson, and Chapman (2004) report that investment policies frequently do not permit leverage, and fewer than 8% of all funds borrow. Similarly, Koski and Pontiff (1999) find that only about 20% of funds use derivatives. 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).

[2] Existing proxies for funding conditions 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 leverage-constrained.

[3] Mathematically, $R_{BAB} = R_L^e/\beta_L - R_H^e/\beta_H$, where R_L^e and R_H^e are excess returns of portfolios of all stocks with market betas below and above the median, respectively.

[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 estimated from mutual funds, LCT could capture the economy-wide desire for leverage.

for firm characteristics in Fama and MacBeth (1973) regressions. Overall, the results provide strong evidence that LCT exposure is an important determinant of the cross-section of stock returns. The strong inverse relation between mutual funds' LCT loadings and future performance is thus inherited from the stocks they hold.

1.1. 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). 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 use leverage implicit 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.

Adrian et al. (2014) and He, Kelly, Manela (2016) empirically test the intermediary-based asset pricing theory of He and Krishnamurthy (2013). While mutual funds are financial intermediaries, the equity capital constraints or the borrowing capacity of He and Krishnamurthy (2013) do not apply to them. In their tests, Adrian et al. (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, while He et al. (2016) use the equity capital ratio of financial intermediaries and extend the analysis to other asset classes. A main determinant of their leverage measure is short-term collateralized borrowing, which is ultimately tied to the cost and availability of borrowing. We measure the unobservable tightness of leverage constraints, which for mutual funds can be binding even if borrowing were available to other market participants.

Chen and Lu (2015) refine the 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 analysis suggests that leverage constraints are important even for investors who face seemingly invariant leverage restrictions.

Fontaine, Garcia, and Gungor (2014) find that a funding liquidity factor derived from 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.

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 (2017) show that benchmarking performance leads asset managers to increase market risk of their investments. We focus not on explaining the determinants of why asset managers shift risk, but argue that these shifts reveal the degree to which leverage constraints bind and affect asset prices. Alankar, Blaustein, and Scholes (2014) generalize Roll (1992) by adding a constraint in the form of a minimum cash level. In their model, 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 constraint binds.

A separate line of mutual fund research has studied performance predictability. 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; Doshi, Elkhami, and Simutin 2015). 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 (2015), 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.

2. Theoretical framework

We present a theoretical framework to support our main argument that mutual funds increase their portfolio risk in response to tightening leverage constraints, while unconstrained investors meet their risk appetite with leverage. This framework extends Black (1972) to accommodate agents with heterogeneous leverage constraints, and is nested in the model of FP.

Consider a two-date economy in which two agents, a mutual fund ($i = m$) and a hedge fund ($i = h$), are endowed with wealth W_m and $W_h = 1 - W_m$, respectively. There is a risk-free asset with return R_f, and agents trade K risky securities that are in positive net supply X and have excess returns R^e and variance-covariance matrix Σ.

Both agents choose portfolio weights ω_i to maximize their quadratic utility over one-period returns with risk aversion parameter γ_i:

$$U_i = \mathbb{E}\left(\omega_i' R^e + R_f\right) - \frac{\gamma_i}{2}\omega_i' \Sigma \omega_i. \tag{1}$$

The mutual fund additionally faces a strict no-borrowing constraint

$$\omega_m' \mathbb{1} \leq 1, \tag{2}$$

where $\mathbb{1}$ denotes a vector of ones. The hedge fund is unconstrained.

It is immediately clear that the unconstrained hedge fund always invests in the tangency portfolio and achieves its desired risk-return tradeoff using leverage. If the leverage constraint for the mutual fund does not bind, it also invests in the tangency portfolio, which then must be the market portfolio. The CAPM holds.

The constraint binds if and only if the mutual fund wants to achieve a higher return than the tangency portfolio. In this case, it picks a portfolio of risky assets on the efficient frontier above the tangency portfolio. Since the market portfolio is a weighted average of both investors' risky asset holdings, its mean must lie between that of the tangency portfolio and that of the mutual fund portfolio. We now derive the equilibrium relation for expected returns to show that they are linearly increasing in beta, which proves that the market beta of the tangency portfolio is less than one, while the mutual fund invests in a portfolio of risky assets with a beta greater than one.

The first-order conditions provide the optimal portfolio weights,

$$\omega_i = \frac{1}{\gamma_i} \Sigma^{-1} (\mathbb{E}R^e - \phi_i \mathbb{1}), \tag{3}$$

where $\phi_h = 0$ and $\phi_m \geq 0$ is the Lagrange multiplier on the constraint.

Market clearing requires that $W_m \omega_m + W_h \omega_h = X$. Define $1/\gamma = W_m/\gamma_m + W_h/\gamma_h$ and $\psi = \frac{W_m}{\gamma_m} \gamma \phi_m$ to obtain

$$\mathbb{E}R^e = \gamma \Sigma X + \psi \mathbb{1} \tag{4}$$

$$= \beta \gamma \mathrm{Var}(R_M^e) + \psi \mathbb{1}, \tag{5}$$

where R_M^e is the excess return of the market portfolio and $\beta = \mathrm{Cov}(R^e, R_M^e)/\mathrm{Var}(R_M^e)$. Summing up Eq. (4) over all assets, we obtain

$$\mathbb{E}R_M^e = \gamma \mathrm{Var}(R_M^e) + \psi. \tag{6}$$

Substitute Eq. (6) into (5) to obtain the pricing relation:

$$\mathbb{E}R^e = \beta(\mathbb{E}R_M^e - \psi) + \psi \mathbb{1}. \tag{7}$$

Eq. (7) shows that expected returns are linearly increasing in beta, but the security market line is flatter than the CAPM predicts. In particular, a zero-beta asset has an excess return of ψ, and the slope of the security market line is $\mathbb{E}R_M^e - \psi$. The distortion relative to the CAPM thus increases in ψ, which in turn depends on the share of wealth of the mutual fund, W_m, and the risk aversions of the two agents. Since the constrained mutual fund holds a portfolio with higher expected returns than the market, this implies that its market beta must exceed one, and its expected return is less than the CAPM suggests. Similarly, the market beta of the tangency portfolio is less than one. The higher the desired beta of the mutual fund, the more costly is the constraint, and the stronger are the distortions relative to the CAPM.

3. Data and the aggregate mutual fund beta

The theory in the previous section predicts that investors who cannot increase explicit leverage due to binding constraints shift their portfolio to riskier securities, thus utilizing the leverage embedded in high-beta assets. Reversing the 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 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 data set, which contains information on stock positions of funds (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. Our sample spans 1980 to 2014.

The theory concerns the risk of holdings of risky assets and not the overall portfolio risk. We therefore 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 end of month t as the sum of (i) the holdings of all funds in our sample that disclosed at the end of month t, (ii) the holdings of funds that disclosed at the end of month $t-1$, adjusted for stock returns in month t, and (iii) holdings disclosed in $t-2$, adjusted for cumulative stock returns in months $t-1$ and t.

We estimate the aggregate fund beta as the weighted sum of individual stocks' market betas. For our main analysis, betas are estimated from daily returns within month t, and are based on Dimson (1979) sum betas using the lag structure suggested by Lewellen and Nagel (2006), which helps to mitigate the effects of asynchronous trading. In the Internet Appendix, we confirm that our findings are robust to estimating individual stock betas over a long horizon of 36 months following the method of FP.

3.1. Treatment of funds' use of leverage

We retain in our sample funds that are permitted to use leverage. While these funds may appear more like the

[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 et al. (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.

unconstrained investor (hedge funds) than the constrained investor (mutual funds) in our model, our motivation to keep them is two-fold. First, even when their investment policies permit borrowing, funds seldom engage in it. In particular, Almazan et al. (2004, p. 297) note that “a portfolio manager [may] adopt a constraint on a purely voluntary basis,” and find that less than half of funds that are permitted to borrow engage in any borrowing. As such, discarding funds that are allowed to use leverage from the analysis will result in a potentially unnecessary reduction in the sample size. Second, identifying such funds cleanly is challenging empirically. When we attempt to do so in the Internet Appendix, we find that our results remain robust to excluding these funds.

3.2. Treatment of cash holdings

The central prediction of our model is that more constrained investors hold higher-beta securities, and so the beta of *risky* asset holdings, rather than of the overall portfolio, reflects the tightness of constraints. For mutual funds, the main difference between the two betas is driven by cash holdings. To dig deeper into the role of cash for the measurement of leverage constraints, it is necessary to understand why mutual funds hold cash. Some cash—for example, the amount held to satisfy outflow requests—can be thought of as ‘non-discretionary’ in the sense that the manager cannot freely spend it to alleviate leverage constraints. In other words, even funds that are not fully invested can face binding constraints because the nature of the mutual fund business requires holding non-discretionary cash. Consequently, explicitly accounting for cash in inferring leverage constraints can result in misleading estimates.

How should the other, ‘discretionary,’ component of cash be treated? From a theoretical perspective, positive discretionary cash holdings indicate that investors are not constrained at all: if they were, they should have chosen a full allocation to risky assets. Put differently, in a model like FP investors would never simultaneously hold high-beta assets and discretionary cash.[6] Negative discretionary cash can be thought of as exacerbating leverage constraints. For example, if cash is below optimum, using it makes the fund more vulnerable to outflow shocks and is thus particularly costly. As such, negative discretionary cash may be interesting to consider, but it is not clear how to infer its level empirically. Consequently, we do not account for cash when computing aggregate beta and instead base the calculation on risky holdings only. Nonetheless, we show in the Internet Appendix that aggregate cash holdings are very stable and therefore have a negligible impact on our analysis.[7]

3.3. Treatment of passive changes in the aggregate mutual fund beta

It might be tempting to conclude that changes in desired risk taking are better revealed by managerial trades than by changes in the beta of their overall stockholdings. However, it is important to recognize that the beta of mutual fund stockholdings can change for three reasons. First, the manager may actively decide to buy or sell assets. Second, the beta may change passively if betas of individual stocks shift. Last, it may change passively as portfolio weights fluctuate with past returns. Thus, just because we observe a manager buying low-beta stocks, it need not imply that risky-asset beta has decreased. In the Internet Appendix, we demonstrate this point with simple numerical examples. As long as managers care about their overall risky-asset beta and have the ability to counteract unwanted passive changes, it is the overall risky-asset beta that is important for our analysis.

In practice, however, managers might not update passive changes to the betas of their stock holdings in real time. To eliminate the impact of possible passive beta changes, we repeat our analysis with a one-month lagged beta. That is, we used current portfolio weights, but stock betas computed one month earlier. The results, summarized in the Internet Appendix, are economically and statistically significant.[8]

3.4. Time series of the aggregate mutual fund beta

Fig. 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 1.08, consistent with the numbers reported in FP. Importantly, the measure exhibits meaningful time variation. The standard deviation is 0.11, and the 10th and 90th percentiles are 0.96 and 1.21, respectively. The volatility of the aggregate beta is decreasing over time, consistent with the mutual fund industry accounting for a growing share of the market. The decrease in volatility does not affect our key tests because they are conditional in nature, using rolling windows of observations.

Interestingly, while prior literature provides strong evidence that funding liquidity dried up during the financial crisis of 2008, the aggregate mutual fund beta remained relatively low during this period. Our interpretation of mutual fund beta as desired leverage is consistent with this evidence, since uncertainty and risk in the market were at all-time highs. All else equal, the optimal portfolio leverage for risk-averse, long-only investors, such as mutual funds, declines with volatility. The two large spikes in the aggregate beta, in October 2006 and January 2011, are also consistent with this interpretation, as they coincide with periods of significant declines in VIX.

[6] In such a model, if a fund had positive discretionary cash, it would have been better off selling its holdings with higher betas and using the proceeds along with the cash to buy low-beta stocks. That way, the fund could maintain the same fund-level beta while reducing the holdings-level beta and hence increasing the expected return of the fund.

[7] Thinking further about the role of cash holdings, changes in discretionary cash could serve as a proxy for LCT. In untabulated results, we find that exposures to innovations in aggregate cash are not priced, suggesting that fluctuations in non-discretionary cash account for a dominant share of the small observable variation in aggregate cash.

[8] Further corroborating robustness is the analysis that uses betas estimated over 36 months of monthly data in the Internet Appendix. Recent changes in beta have negligible impact on the long-horizon beta estimates.

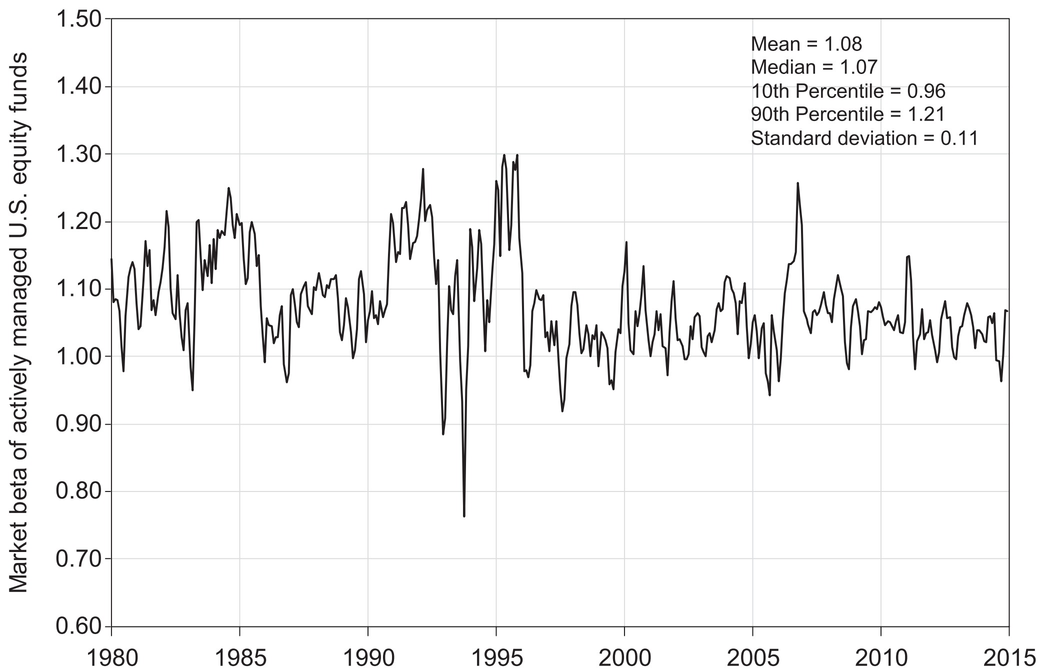

Fig. 1. Leverage constraint tightness. This figure plots the three-month moving average of leverage constraint tightness, computed as market beta of the aggregate holdings of all actively managed U.S. equity mutual funds. We calculate the holdings of the aggregate mutual fund at the end of month t as the sum of (i) the holdings of all funds in our sample that disclosed at the end of month t, (ii) the holdings of funds that disclosed at the end of month $t-1$, adjusted for the stock returns in month t, and (iii) holdings disclosed in $t-2$, adjusted for the cumulative stock returns in months $t-1$ and t. The aggregate fund beta is the weighted sum of individual stocks' market betas, estimated from a standard market model using daily returns within month t and the Lewellen and Nagel (2006) lag structure to reduce biases due to non-synchronous trading.

We cannot rule out that some movement in the aggregate beta is driven by measurement error. For example, negative spikes we observe around December 1992 and October 1993 do not coincide with jumps in VIX or other proxies for funding conditions we considered. We expect that noise in our measure of aggregate beta mutes the significance of our results. Correspondingly, we show in the Internet Appendix that our findings are robust when we treat the outliers directly, by winsorizing either the time series of LCT or the cross-section of individual stock betas used in LCT calculation. Overall, the evidence suggests that both measurement error and changes in the desired leverage contribute to fluctuations in the aggregate beta.

4. Leverage constraint tightness

The theoretical link between the aggregate mutual fund beta and leverage constraint tightness is well-motivated. We now show empirically that the aggregate mutual fund beta co-moves with known proxies for funding conditions, and, consistent with theory, robustly predicts returns of the BAB factor, thus validating it as an empirical proxy for LCT. We also discuss alternative explanations for time variation in mutual fund beta, and argue that all of them support our interpretation of beta as a measure of LCT.

4.1. Aggregate mutual fund beta and funding conditions

We begin by studying the empirical relation between our LCT measure and known proxies for funding conditions. We consider seven proxies: broker-dealer asset growth, broker-dealer leverage, bond-implied funding liquidity, the TED spread, the VIX index, as well as two measures for stock market liquidity. 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 et al. (2014) follow this idea by proposing a broker-dealers' leverage factor. Fontaine and Garcia (2012) measure funding illiquidity from the cross-section of Treasury securities. The TED spread, the difference between the London Interbank Offered Rate (LIBOR) and the T-bill rate, is frequently used to proxy for borrowing cost (e.g., Gârleanu and Pedersen, 2011; FP). Further, it is well documented that funding conditions change with aggregate uncertainty, as proxied by the VIX (Ang et al., 2011). Since funding conditions are linked to market liquidity (Brunnermeier and Pedersen, 2009), we also consider the Pástor and Stambaugh (2003) liquidity factor as well as the Sadka (2006) permanent price-impact factor.

We are interested in how shocks to funding liquidity relate to LCT. We use quarterly observations since broker-dealer asset growth and leverage are not available at a higher frequency. We identify shocks as innovations from the best model in the autoregressive moving average (*ARMA*) class. In particular, for each series, we estimate *ARMA*(p, q) models, $0 \le p, q \le 3$, and select the model that minimizes Akaike's Information Criterion (AIC).

Table 1
Correlations of leverage constraint tightness and proxies of funding conditions.
This table reports the correlation matrix of quarterly innovations in leverage constraint tightness with those of the broker-dealers' leverage factor, the Treasury security-based funding liquidity measure, broker-dealers' asset growth rate, the TED spread, the VIX index, the Pástor and Stambaugh (2003) factor, and the Sadka (2006) permanent price-impact factor. Innovations in leverage constraint tightness in (1a) are calculated from the $AR(1)$ model. All other innovations are obtained from the $ARMA(p, q)$ model, $0 \le p, q \le 3$, with the lowest AIC. We sign all proxies such that positive shocks indicate a worsening of funding conditions. Significant correlations are indicated by an asterisk. The sample period is 1980 to 2014, except for broker-dealer leverage (ending in 2012), bond-implied funding liquidity, the TED spread, and the VIX index (all starting in 1986), and the Sadka factor (1983–2012) due to data availability.

Variable		(p, q)	(1a)	(1b)	(2)	(3)	(4)	(5)	(6)	(7)
(1a)	Leverage constraint tightness	(1,0)								
(1b)	Leverage constraint tightness	(1,3)	0.94*							
(2)	−1×Broker-dealer asset growth	(3,3)	0.14*	0.13*						
(3)	−1×Broker-dealer leverage factor	(3,2)	−0.04	−0.05	0.52*					
(4)	Bond-implied funding liquidity	(3,1)	0.15*	0.19*	0.25*	0.19*				
(5)	TED spread	(1,1)	−0.01	0.01	−0.05	−0.37*	0.30*			
(6)	VIX	(1,1)	−0.15*	−0.12*	0.18*	0.04	0.28*	0.30*		
(7)	−1×Pastor-Stambaugh factor	(1,0)	0.04	0.02	0.29*	0.15*	0.08	0.09	0.38*	
(8)	−1×Sadka factor	(0,0)	0.06	0.07	0.10	−0.10	0.31*	0.52*	0.42*	0.21*

For LCT, the best fitting model is $ARMA(1,3)$. To address potential overfitting of the LCT series, we additionally obtain innovations from a more parsimonious $AR(1)$ model. In both cases, LCT innovations have a negligible autocorrelation (0.01 and -0.01, respectively). We sign all proxies so that positive shocks indicate worsening of funding conditions.

Table 1 shows the pairwise correlations between shocks to funding or market liquidity and LCT. Both measures of LCT innovations are significantly and positively correlated with the negative broker-dealer asset growth (0.14 and 0.13) and with the bond liquidity factor (0.15 and 0.19). The near zero correlation with the TED spread in particular is not surprising, since the TED spread measures the cost of borrowing, which does not directly impact mutual funds. Overall, the correlations suggest that increases in our LCT proxy are associated with deteriorating funding conditions.

The significant negative correlation with the 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.[9] On the other hand, investors actively managing risk want to reduce leverage in times of heightened aggregate volatility, and therefore their desire to borrow declines. The negative correlation with the VIX is therefore consistent with our interpretation 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.

4.2. Leverage constraint tightness and betting-against-beta profits

The relation between LCT and BAB warrants a more detailed discussion. FP show theoretically that the future BAB premium increases when leverage constraints tighten (their Eq. (12)). Empirically, however, they find that the level of the TED spread forecasts BAB negatively. We now test this prediction using our LCT measure.

[9] For example, Ang et al. (2011) show that the leverage of hedge funds is negatively related to the VIX.

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 one, six, or 12 months on the lagged leverage constraint tightness measure. Panel B groups the months in the sample into halves by leverage constraint tightness and summarizes future BAB factor returns, shown in percent monthly. The sample period is 1980 to 2014.

Panel A: Regressions	Dependent variable: BAB return over		
	1 month	6 months	12 months
Lagged LCT, 1 month	0.011	0.017	0.022
t-statistic	[0.77]	[1.82]	[2.41]
Adjusted R^2	0.14	0.72	2.02
Lagged LCT, 6 months	0.051	0.070	0.084
t-statistic	[1.65]	[3.16]	[4.05]
Adjusted R^2	0.49	4.62	10.64
Lagged LCT, 12 months	0.089	0.117	0.124
t-statistic	[2.67]	[4.34]	[4.62]
Adjusted R^2	1.35	9.64	16.71
Panel B: Sorts	Average monthly BAB return over		
	1 month	6 months	12 months
LCT during last 1 month is			
Low	0.71	0.65	0.67
High	1.18	1.15	1.12
LCT during last 6 months is			
Low	0.71	0.71	0.63
High	1.18	1.09	1.17
LCT during last 12 months is			
Low	0.52	0.50	0.51
High	1.37	1.30	1.29

Panel A of Table 2 presents regressions in which the dependent variable is the monthly BAB return over one, six, and 12 months. The explanatory variables are the lagged monthly level as well as six- and 12-month moving averages of LCT. We find that our LCT proxy is positively related to future BAB returns, as the theory of FP suggests. The predictive power is particularly pronounced when we use moving averages to smooth the LCT estimates. In these cases, all coefficients are significantly positive, and the R^2 approaches 17% for 12-month-ahead regressions.

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 $t+1$ on the following variables measured at the end of t: the 12-month moving average of leverage constraint tightness, the broker-dealer year-over-year asset growth rate, the level of broker-dealer leverage calculated by cumulating the factor realizations with time trend removed, bond-implied funding liquidity, the TED spread, the VIX index, the Pástor and Stambaugh (2003) liquidity factor, and the 12-month moving average of the Sadka (2006) permanent price-impact measure. The sample period is 1980 to 2014, except for broker-dealer leverage (ending in 2012), bond-implied funding liquidity, the TED spread, and the VIX index (all starting in 1986), and the Sadka factor (1983–2012) due to data availability.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage constraint tightness	0.124									0.118
	[4.62]									[4.89]
−1× Broker-dealer asset growth		−0.015							−0.007	−0.010
		[−1.45]							[−0.70]	[−1.21]
−1× Broker-dealer leverage level			0.004						0.006	0.004
			[0.97]						[1.37]	[1.10]
Bond-implied funding liquidity				−0.004					−0.002	−0.000
				[−2.98]					[−1.15]	[−0.08]
TED spread					−0.012				−0.011	−0.016
					[−3.84]				[−2.60]	[−3.63]
VIX						−0.001			−0.000	−0.000
						[−2.74]			[−1.74]	[−0.17]
−1 × Pastor-Stambaugh factor							−0.024		0.006	0.002
							[−1.33]		[0.37]	[0.15]
−1×Sadka factor								−0.626	1.995	1.575
								[−1.35]	[3.06]	[2.39]
Adjusted R^2	16.71	1.38	0.69	6.48	12.12	6.69	0.83	0.24	16.08	27.03

Panel B of the table illustrates the economic magnitude of these relations. We split our sample of 420 months into two equal groups by the explanatory variables. Following times of non- or weakly binding constraints (low LCT), the future one-month BAB return is 0.71%, while it is much larger, 1.18%, after periods of tight leverage constraints. The relation is similar over horizons of up to 12 months. When splitting the sample instead by the less noisy 12-month moving average of LCT, the results get even stronger, with BAB returns following tight leverage constraints about 80 basis points higher than those after times of only weakly binding constraints.

It is conceivable that the aggregate demand for beta by mutual funds drives up prices of high-beta assets, and the BAB predictability we document is a consequence of price pressure. Two observations cast doubt on this explanation. First, we find that LCT equally strongly predicts profits of BAB-like factors constructed using subsets of stocks with low or high mutual fund ownership.[10] Second, the predictability persists for horizons of up to 12 months, and the estimates in Panel B of Table 2 vary little with horizon. The effect thus lasts longer than what would be expected if it were due to easing of price pressure.

In Table 3, we compare the ability of LCT and other funding and market 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. None of the other variables is significantly positive in univariate specifications. In fact, bond-implied funding liquidity, the TED spread, and the VIX enter significantly with a theoretically incorrect negative sign. In the multivariate test, only LCT and the Sadka (2006) permanent price-impact factor are significant, and the multivariate R^2 reaches 27%.

The strong predictability of BAB provides empirical support to the theory 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.

4.3. *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. At the same time, these arguments make no predictions about the beta of risky asset

[10] For the 12-month predictability of a BAB-like factor constructed using stocks with high mutual fund ownership, we obtain a coefficient of 0.118 ($t=3.90$) and a R^2 of 17.63%. For stocks with low ownership, the coefficient is 0.149 ($t=3.94$) and the R^2 of 14.06%.

holdings 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.[11] 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 a theory that makes predictions about overall portfolio risk, an increase in beta of risky asset holdings will correspond to tighter leverage constraints.[12]

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 leverage constraints become more binding.

Second, managers might try to time the cross-sectional beta risk premium, the relative performance of high- and low-beta stocks that is unrelated to overall market performance.[13] For example, if the cross-sectional beta risk premium is lower than the market risk premium, then low-beta stocks have positive expected alphas, and managers should decrease the average beta of their holdings. In turn, a low aggregate mutual fund beta should be followed by strong performance of low-beta stocks. Our empirical evidence contradicts this interpretation. In particular, we show that low aggregate mutual fund beta is followed by strong performance of high-beta stocks, as evidenced by low BAB factor returns.

Overall, the evidence strongly supports our interpretation of aggregate mutual fund beta. We cannot exclude that for some stock-picking managers the beta of their portfolio 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.

5. 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 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 inversely 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, 5% annually, and remains robust after controlling for existing predictors of fund performance and measures of managerial skill.

5.1. 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

$$R^e_{i,\tau} = \alpha_{i,t} + \beta^{MKT}_{i,t} R^e_{MKT,\tau} + \beta^{LCT}_{i,t} \Delta^{LCT}_{\tau} + \varepsilon_{i,\tau} \qquad \tau \in \{t-23, t\}, \tag{8}$$

where $R^e_{i,\tau}$ and $R^e_{MKT,\tau}$ are the excess returns of fund i and the market in month τ and Δ^{LCT}_{τ} is the innovation in leverage constraint tightness. We compute innovations Δ^{LCT}_{τ} as residuals from an $AR(1)$ model using data up to and including month t so as to avoid a look-ahead bias. To obtain meaningful risk loadings, we require each fund to have non-missing returns in at least 12 months of the 24-month estimation period.

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

We find that raw and factor-adjusted future fund returns decline with LCT loadings. The magnitude of the effect is economically large. For example, the decile of funds with the lowest LCT exposures generates monthly excess

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

[12] If beta instead measured 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 if investment opportunities are good, as indicated by 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.

[13] In our model, the wedge between the cross-sectional beta risk premium and the market risk premium is affected by the relative wealth of the constrained investor, the mutual fund industry. Naturally, as there are more constrained investors, the constraints will have more impact and decrease the cross-sectional beta risk premium relative to market risk premium.

[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.

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 innovations in leverage constraint tightness. Newey and West (1987) t-statistics are in square brackets. Funds are assigned into groups at the end of every month t, and the 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 1981 to 2014.

	Excess	Alphas from			5-factor loadings				
Portfolio	return	CAPM	4-factor	5-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{PS}
Panel A: Net-of-expenses returns									
Low	0.79	0.15	0.13	0.16	1.01	−0.01	0.20	0.03	−0.05
	[3.12]	[1.37]	[1.21]	[1.44]	[39.5]	[−0.20]	[5.60]	[1.17]	[−1.87]
2	0.63	0.00	−0.01	0.01	1.00	−0.03	0.13	0.03	−0.03
3	0.62	−0.01	−0.02	−0.01	1.00	−0.02	0.08	0.03	−0.03
4	0.56	−0.06	−0.05	−0.05	0.99	−0.04	0.07	0.01	−0.02
5	0.53	−0.10	−0.09	−0.07	1.00	−0.06	0.08	0.02	−0.03
6	0.58	−0.06	−0.03	−0.02	0.99	−0.08	0.13	0.01	−0.01
7	0.48	−0.16	−0.11	−0.11	0.99	−0.11	0.14	0.00	0.00
8	0.51	−0.14	−0.11	−0.11	1.00	−0.09	0.17	0.02	0.00
9	0.49	−0.19	−0.13	−0.13	1.04	−0.17	0.25	0.02	0.00
High	0.39	−0.32	−0.25	−0.25	1.06	−0.20	0.34	0.03	0.01
	[1.41]	[−2.98]	[−2.80]	[−2.82]	[50.2]	[−6.24]	[11.5]	[1.37]	[0.38]
Low-High	0.40	0.47	0.38	0.41	−0.05	0.19	−0.14	0.00	−0.06
	[2.61]	[3.04]	[2.47]	[2.66]	[−1.35]	[3.18]	[−2.53]	[0.02]	[−1.39]
Panel B: Quintiles									
Low-High	0.32	0.38	0.30	0.32	−0.04	0.16	−0.14	0.00	−0.04
	[2.55]	[3.01]	[2.46]	[2.59]	[−1.31]	[3.30]	[−2.99]	[−0.09]	[−1.18]
Panel C: Halves									
Low-High	0.14	0.17	0.12	0.14	−0.01	0.09	−0.10	0.00	−0.03
	[2.23]	[2.59]	[1.98]	[2.16]	[−0.46]	[3.70]	[−4.30]	[0.25]	[−1.59]
Panel D: Gross-of-expenses returns									
Low-High	0.40	0.47	0.38	0.41	−0.05	0.19	−0.14	0.00	−0.06
	[2.62]	[3.06]	[2.48]	[2.67]	[−1.35]	[3.18]	[−2.53]	[0.02]	[−1.39]
Panel E: Controlling for BAB when estimating β^{LCT}									
Low-High	0.33	0.37	0.35	0.39	−0.05	0.04	−0.08	0.00	−0.07
	[2.54]	[2.81]	[2.63]	[2.81]	[−1.50]	[0.79]	[−1.56]	[0.10]	[−1.74]
Panel F: Using 60 months to estimate betas									
Low-High	0.32	0.39	0.32	0.30	−0.07	0.16	−0.05	−0.01	0.02
	[2.53]	[2.99]	[2.42]	[2.32]	[−1.94]	[3.11]	[−0.95]	[−0.33]	[0.65]

returns of 0.79%, while the highest decile earns just 0.39%. The difference is statistically significant at 0.40% per month ($t=2.61$), or approximately 5% annually. Factor adjustment has little impact on the performance differential. In particular, the difference in five-factor alphas of the two groups, at 0.41% per month ($t=2.66$), is again very large, especially given that we are comparing portfolios of diversified mutual funds. Most studies of mutual fund performance predictability document considerably smaller return differentials.[15] The last five columns of Table 4 show loadings on the five factors. The low-high portfolio loads positively on the value factor and negatively on size, but is not significantly related to the market, momentum, or liquidity factors.

In Panels B and C, we show the returns of the spread portfolio when funds are ranked into five or two groups, respectively. As expected, the economic magnitude declines as focus moves away from the tails of the distribution. The difference in five-factor alphas is 0.32% ($t=2.59$) when quintiles are used, and 0.14% ($t=2.16$) between halves. Due to increased diversification within the bigger groups, all estimates remain statistically significant.

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

If FP's betting-against-beta factor performs well, the portfolio weight of low-beta stocks increases, and hence LCT declines mechanically. To account for this correlation, in Panel E we control for the BAB factor when we estimate the LCT exposures. The resultant five-factor alpha of the spread portfolio is 0.39% per month and statistically significant, suggesting that exposure to BAB does not drive our results.

[15] 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, R-squared, and active weight range between 0.17% and 0.32% per month (Kacperczyk et al., 2005, 2008; Cremers and Petajisto, 2009; Amihud and Goyenko, 2013; Doshi et al., 2015, respectively).

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 innovations in leverage constraint tightness. Newey and West (1987) t-statistics are in square brackets. The back-testing methodology follows Mamaysky et al. (2008): For a fund to be included in a portfolio in month $t+2$, its return in month $t+1$ must be below (above) the cross-sectional median if its loading estimated at the end of month t is above (below) the cross-sectional median. The five factors are market (MKT), value (HML), size (SMB), momentum (UMD), and Pastor-Stambaugh liquidity (PS). The sample period is 1981 to 2014.

	Excess	Alphas from			5-factor loadings				
Portfolio	return	CAPM	4-factor	5-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{PS}
Panel A: Net-of-expenses returns									
Low	0.89	0.28	0.24	0.27	0.93	−0.02	0.33	0.06	−0.06
	[3.56]	[2.25]	[2.06]	[2.33]	[34.2]	[−0.44]	[8.61]	[2.52]	[−2.12]
2	0.79	0.17	0.15	0.17	0.95	−0.05	0.24	0.06	−0.04
3	0.73	0.12	0.10	0.12	0.96	−0.02	0.14	0.04	−0.04
4	0.62	0.02	0.00	0.01	0.95	−0.04	0.17	0.05	−0.01
5	0.68	0.07	0.06	0.07	0.96	−0.04	0.11	0.04	−0.01
6	0.47	−0.18	−0.17	−0.16	1.03	−0.03	0.09	0.00	−0.01
7	0.40	−0.25	−0.19	−0.20	1.01	−0.10	0.14	−0.02	0.01
8	0.38	−0.30	−0.25	−0.26	1.07	−0.09	0.10	−0.01	0.03
9	0.40	−0.30	−0.22	−0.22	1.06	−0.16	0.18	0.00	−0.01
High	0.33	−0.40	−0.34	−0.35	1.12	−0.14	0.23	−0.01	0.02
	[1.17]	[−3.88]	[−3.44]	[−3.53]	[48.0]	[−3.89]	[7.03]	[−0.25]	[0.93]
Low-High	0.56	0.68	0.58	0.62	−0.18	0.12	0.10	0.07	−0.09
	[3.31]	[4.06]	[3.39]	[3.60]	[−4.28]	[1.83]	[1.65]	[1.73]	[−1.84]
Panel B: Quintiles									
Low-High	0.48	0.58	0.48	0.51	−0.14	0.11	0.08	0.06	−0.06
	[3.42]	[4.13]	[3.39]	[3.54]	[−3.90]	[2.05]	[1.55]	[1.84]	[−1.43]
Panel C: Halves									
Low-High	0.30	0.37	0.30	0.32	−0.09	0.07	0.01	0.05	−0.04
	[3.40]	[4.25]	[3.44]	[3.59]	[−4.07]	[1.96]	[0.42]	[2.46]	[−1.47]
Panel D: Gross-of-expenses returns									
Low-High	0.56	0.68	0.57	0.62	−0.18	0.12	0.10	0.07	−0.09
	[3.31]	[4.05]	[3.39]	[3.58]	[−4.28]	[1.82]	[1.66]	[1.73]	[−1.83]
Panel E: Controlling for BAB when estimating β^{LCT}									
Low-High	0.50	0.58	0.54	0.58	−0.14	−0.01	0.11	0.06	−0.08
	[3.07]	[3.56]	[3.25]	[3.46]	[−3.32]	[−0.13]	[1.85]	[1.61]	[−1.79]
Panel F: Using 60 months to estimate betas									
Low-High	0.54	0.65	0.56	0.57	−0.17	0.11	0.15	0.05	−0.02
	[3.24]	[3.91]	[3.30]	[3.34]	[−3.91]	[1.73]	[2.47]	[1.16]	[−0.44]

Lastly, in Panel F we use 60-month windows to estimate β^{LCT}. These longer windows provide less timely beta estimates. Consequently, the performance differential declines to 0.30%, but nonetheless remains significant.

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.

5.2. Back-tested mutual fund performance

The risk loadings obtained from regression (8) are estimated with noise. As a result, the top and bottom β^{LCT} deciles might be populated not just by the funds with the highest and lowest LCT loadings, but also by funds with the largest estimation errors. One way to reduce the impact of estimation errors 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 building on Kacperczyk et al. (2008), Dong and Massa (2013), and Dong et al. (2015). As before, we first calculate LCT betas of all funds at the end of month t. However, instead of investing in β^{LCT}-sorted portfolios 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-median LCT betas, we therefore expect below-median returns. If instead we observe above-median returns, there is an increased chance that the LCT beta was affected by estimation error. Consequently, we only keep funds with high estimated LCT loadings and low returns or with low estimated loadings and high returns, rank them into deciles, and hold the portfolios 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 standard factor adjustment does not reduce this effect. However, the back-testing procedure yields considerably wider spreads in future returns of the β^{LCT}-sorted portfolios. Panel A shows that the spread

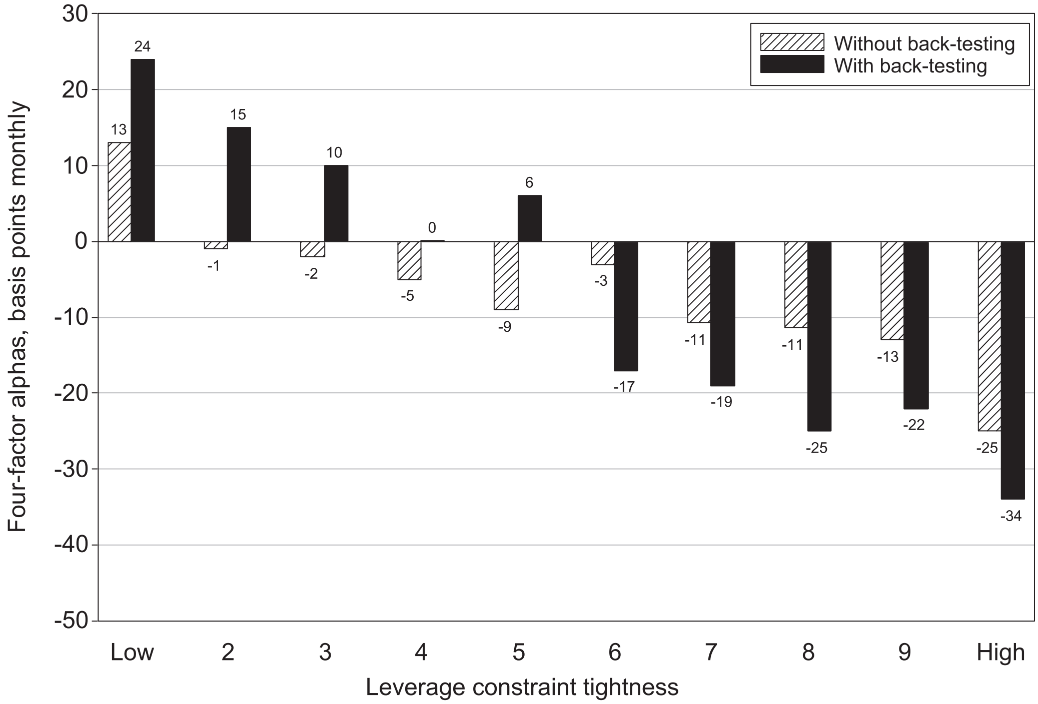

Fig. 2. Performance of leverage constraint tightness portfolios: Mutual funds. This figure plots average four-factor alphas, in basis points per month, for the portfolios of actively managed U.S. equity funds sorted by their loadings on innovations in leverage constraint tightness. The striped bars show performance measures obtained from the simple sort, and the solid 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 portfolios are held during month $t+1$. The back-testing methodology follows Mamaysky et al. (2008): For a fund to be included in a portfolio in month $t+2$, its return in month $t+1$ must be below (above) the cross-sectional median if its loading estimated at the end of month t is above (below) the cross-sectional median. The sample period is 1981 to 2014.

expands by around 0.20% monthly relative to the case without back-testing. For example, the difference in five-factor alphas of the low- and high-exposure portfolios reaches 0.62% monthly, economically very large and statistically significant ($t=3.60$). Moreover, alphas of the low-β^{LCT} portfolio are not only positive, but also highly significant. This result, uncommon in the literature, allows investors to profit from long-only investments in those funds.[16] The remaining panels of Table 5 mirror those in Table 4, highlighting the robust nature of the relation between LCT betas and future fund performance.

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

[16] Many cross-sectional studies of predictability of mutual fund performance find that alphas computed with net-of-expenses returns, while predictable, are not significantly positive. See, for example, Table II in Kacperczyk et al. (2005), Table 4 in Kacperczyk et al. (2008), or Panel A in Table 2 of Amihud and Goyenko (2013).

5.3. 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, such as the industry concentration ratio of Kacperczyk et al. (2005), active share of Cremers and Petajisto (2009), and active weight of Doshi et al. (2015), or compare fund returns against benchmark returns, such as the return gap of Kacperczyk et al. (2008), and R-squared of Amihud and Goyenko (2013). Skill can also be seen in prior fund return ((Hendricks, Patel, and Zeckhauser, 1993; Bollen and Busse, 2005), and fund turnover (Pástor, Stambaugh, and Taylor, 2017). Building on the theoretical insights of Berk and Green (2004), Berk and Binsbergen (2015) argue that money should flow to skilled managers as long as their marginal value added is positive. Under this view, skill can be measured by fund size.

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.

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 innovations 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 returns of each group are then calculated in month $t+1$. The back-testing methodology follows Mamaysky et al. (2008): For a fund to be included in a portfolio in month $t+2$, its return in month $t+1$ must be below (above) the cross-sectional median if its loading estimated at the end of month t is above (below) the cross-sectional median. The sample period is 1981 to 2014, 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	0.23	[2.06]	0.46	[2.86]	0.44	[3.52]	0.69	[3.40]
Return gap	0.31	[2.22]	0.43	[2.39]	0.52	[2.97]	0.62	[3.38]
Active share	0.32	[2.29]	0.40	[2.40]	0.42	[2.70]	0.61	[3.28]
R-squared	0.34	[2.31]	0.39	[2.41]	0.48	[2.75]	0.65	[3.43]
Active weight	0.37	[2.46]	0.34	[2.32]	0.55	[3.11]	0.59	[3.19]
Return runup	0.30	[2.24]	0.39	[2.41]	0.50	[3.22]	0.61	[3.37]
Turnover	0.40	[2.60]	0.29	[2.16]	0.57	[3.23]	0.58	[3.39]
Fund size	0.37	[2.43]	0.34	[2.32]	0.60	[3.32]	0.56	[3.25]

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 more or less skilled, funds with low exposure to LCT innovations outperform high-exposure funds by a significant margin, between 0.23% and 0.69% monthly. The predictability of mutual fund performance that we uncover is thus distinct from the results documented in the prior literature on managerial skill.

6. 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 loadings on leverage constraint tightness significantly forecast returns at the firm level.[17] Mutual fund performance related to LCT exposure is thus inherited from the stocks they hold.

[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.

6.1. Determinants of leverage constraint tightness loadings

Before exploring the pricing implications of leverage constraint tightness in the cross-section of stocks, we would like to understand the characteristics of stocks with different return exposures to changes in LCT. To do this, we estimate monthly risk loadings β^{LCT} as slope coefficients from rolling time-series regressions of individual security excess returns on changes in LCT, as in Eq. (8). Our sample consists of all common stocks on CRSP listed on the NYSE, Amex, or Nasdaq.[18]

Table 7 reports results of panel regressions of stock-level LCT exposure on firm and stock characteristics. All regressions include time and industry (Fama-French 49) fixed effects, and cluster standard errors by stock and time. In specifications (1) and (2) we explore the mechanical relation between β^{LCT} and market and BAB factor exposures. The two variables enter with the expected signs, indicating that if high-beta stocks perform well relative to low-beta stocks, the changing portfolio weights increase the aggregate mutual fund beta.

In specification (3), we find a strong positive relation between institutional ownership and β^{LCT}. This result suggests that institutions buy stocks that provide high payoffs when leverage constraints tighten. They thus appear to be actively hedging their exposure to changes in LCT.

As the evidence in Table 1 indicates, leverage constraints tighten when funding conditions deteriorate. Firms with higher financial leverage can be expected to be more sensitive to changes in funding conditions as they interact with capital markets more frequently. The negative coefficient in regression (4) confirms that firms with more lever-

[18] Our results are robust to excluding financial firms and utilities and to imposing a minimum price filter.

Table 7
Determinants of stock-level leverage constraint tightness loadings.
This table reports results of panel regressions of stock-level loadings on innovations in leverage constraint tightness, β^{LCT}, on that stock's market beta, beta with respect to the betting-against-beta (BAB) factor, institutional ownership, financial leverage computed as the sum of long- and short-term debt divided by market equity, log of market equity, log of the book-to-market ratio, gross profits-to-assets ratio, year-over-year asset growth rate, 11-month stock return runup computed as of the end of month $t-1$, return reversal computed as month t stock return, idiosyncratic volatility computed as residual standard deviation from month t three-factor regressions on daily data, turnover, and the Amihud (2002) illiquidity measure. With the exception of stock return runup, all variables are computed at the end of every month t. Regressions include time and industry fixed effects, where industry classification is based on 49 Fama-French industries. The t-statistics in square brackets are based on standard errors clustered by stock and time. The sample period is 1981 to 2014.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Market beta	0.009	−0.007	−0.008	−0.008	−0.011	−0.012
	[1.96]	[−2.07]	[−2.50]	[−2.26]	[−2.76]	[−2.91]
BAB factor beta		−0.030	−0.029	−0.028	−0.028	−0.027
		[−7.87]	[−7.12]	[−6.66]	[−6.01]	[−5.52]
Institutional ownership			0.043	0.040	0.032	0.037
			[5.23]	[4.78]	[3.30]	[3.73]
Financial leverage				−0.007	−0.007	−0.009
				[−5.43]	[−5.31]	[−5.56]
Log market equity					−0.000	0.000
					[−0.06]	[0.09]
Log book-to-market ratio					−0.010	−0.010
					[−3.38]	[−2.97]
Gross profits-to-assets					−0.029	−0.029
					[−1.41]	[−1.15]
Asset growth					0.0117	0.0114
					[2.64]	[2.49]
Stock return runup						−0.008
						[−0.74]
Stock return reversal						−0.018
						[−0.47]
Idiosyncratic volatility						−0.041
						[−1.28]
Turnover						−0.000
						[−0.18]
Amihud illiquidity						−0.342
						[−1.12]
Adjusted R^2	6.60	8.41	8.77	9.01	9.63	10.24

age have particularly low returns when funding conditions worsen.

In regression (5), we add firm size, book-to-market, profitability, and asset growth as controls. We find that growth firms have higher LCT exposures, as evidenced by the negative coefficient on book-to-market and the positive coefficient on asset growth. This is consistent with investors attempting to overcome their explicit leverage constraints by using the leverage embedded in growth options.

The final specification shows that many stock market measures, such as prior returns, idiosyncratic volatility, and liquidity, are unrelated to LCT exposure. While the regression R^2 of 10.24% indicates that a lot of the variation in β^{LCT} is unexplained by the firm and stock characteristics considered, the significant coefficients we observe are consistent with theoretical predictions and support our interpretation of aggregate beta as a measure of LCT.

6.2. Cross-sectional return predictability

To analyze the pricing of LCT in the cross-section of stocks, we form portfolios based on the estimated β^{LCT} and examine returns in the month following the estimation period. We summarize the results of this portfolio analysis in Table 8. Panel A shows that the value-weighted quintile of stocks with low LCT loadings generates excess returns of 0.77% monthly, while the quintile with high loadings earns just 0.23%. The difference of 0.54% is economically large and statistically significant (t=2.86). 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. They are positive for the low-exposure portfolio and are strongly negative for the high-exposure group. The difference, ranging from 0.41% to 0.62%, is always statistically significant.

The last five columns contain 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. The low-high hedge portfolio loads negatively on market risk and positively on the HML, and is unrelated to size, momentum, and liquidity factors.

In the remaining panels, we evaluate robustness by varying portfolio formation and weighting schemes. We repeat the analysis for the low-high portfolio using equal-

Table 8
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 innovations in leverage constraint tightness. Newey and West (1987) t-statistics are in square brackets. Stocks are assigned into groups at the end of every month t, and the value-weighted (Panels A, C, E, G, H) 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 1981 to 2014.

	Excess	Alphas from			5-factor loadings				
Portfolio	return	CAPM	4-factor	5-factor	β^{MKT}	β^{HML}	β^{SMB}	β^{UMD}	β^{PS}
Panel A: Quintiles, value-weighted									
Low	0.77	0.05	0.04	0.05	1.12	0.00	0.36	0.01	−0.03
	[2.64]	[0.35]	[0.27]	[0.39]	[36.2]	[−0.04]	[8.26]	[0.26]	[−0.91]
2	0.82	0.20	0.17	0.18	1.01	0.08	0.04	−0.01	−0.02
3	0.68	0.13	0.05	0.07	0.94	0.16	−0.12	0.02	−0.03
4	0.57	−0.04	0.00	−0.01	0.99	0.00	−0.11	−0.05	0.01
High	0.23	−0.57	−0.38	−0.39	1.17	−0.29	0.32	−0.09	0.03
	[0.73]	[−4.34]	[−3.25]	[−3.35]	[42.6]	[−6.99]	[8.17]	[−3.38]	[0.96]
Low-High	0.54	0.62	0.41	0.44	−0.05	0.29	0.04	0.09	−0.06
	[2.86]	[3.22]	[2.17]	[2.31]	[−1.09]	[3.81]	[0.61]	[2.01]	[−1.09]
Panel B: Quintiles, equal-weighted									
Low-High	0.39	0.46	0.31	0.31	−0.04	0.21	−0.01	0.07	−0.01
	[3.45]	[3.99]	[2.76]	[2.77]	[−1.44]	[4.85]	[−0.33]	[2.51]	[−0.32]
Panel C: Halves, value-weighted									
Low-High	0.31	0.32	0.23	0.24	0.01	0.14	0.08	0.04	−0.03
	[3.51]	[3.53]	[2.55]	[2.62]	[0.50]	[3.85]	[2.29]	[1.68]	[−1.07]
Panel D: Halves, equal-weighted									
Low-High	0.25	0.27	0.19	0.20	−0.02	0.11	0.02	0.04	−0.01
	[3.89]	[4.27]	[3.06]	[3.10]	[−0.97]	[4.67]	[0.68]	[2.46]	[−0.69]
Panel E: Deciles, value-weighted									
Low-High	0.62	0.71	0.51	0.54	−0.08	0.32	0.07	0.06	−0.07
	[2.58]	[2.90]	[2.11]	[2.20]	[−1.22]	[3.24]	[0.78]	[0.97]	[-0.93]
Panel F: Deciles, equal-weighted									
Low-High	0.43	0.50	0.37	0.37	−0.05	0.26	−0.07	0.02	−0.01
	[2.97]	[3.43]	[2.56]	[2.57]	[-1.32]	[4.55]	[-1.39]	[0.46]	[-0.19]
Panel G: Controlling for BAB when estimating β^{LCT}									
Low-High	0.37	0.37	0.42	0.46	−0.02	0.00	0.03	−0.06	−0.09
	[2.19]	[2.18]	[2.33]	[2.52]	[−0.46]	[−0.02]	[0.39]	[−1.37]	[−1.57]
Panel H: Using 60 months to estimate β^{LCT}									
Low-High	0.48	0.48	0.38	0.33	0.02	0.11	0.09	0.07	0.09
	[3.00]	[3.06]	[2.37]	[2.10]	[0.38]	[1.77]	[1.56]	[1.88]	[2.04]

weighted quintile returns (Panel B), as well as splitting the sample in halves (C and D) or deciles (E and F). As in the tests with mutual funds, Panels G and H vary the estimation procedure for β^{LCT} by controlling for the BAB factor and changing the length of the estimation window. In all cases, the difference portfolio has economically large and statistically significant returns. In many cases, the t-statistics on the performance differentials exceed 3.0, clearing not only conventional levels of significance, but also the more stringent hurdle suggested by Harvey, Liu, and Zhu (2016) to account for data mining.

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, gross profitability, and idiosyncratic volatility.[19] In Table 9, we use Fama and MacBeth (1973) regressions to investigate whether these characteristics subsume the predictive ability of LCT exposure.

Regression (1) confirms the negative predictive power of β^{LCT}. The estimated price of LCT risk is negative at -0.13% monthly. All independent variables are normalized so that each month, the cross-sectional standard deviation is one. The coefficient therefore implies that a one standard deviation increase in LCT exposure results in a 0.13% decrease in future monthly return. In the remaining regressions, we augment β^{LCT} by firm characteristics. In all cases, our coefficient of interest remains significantly negative.[20]

Overall, the results from 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 con-

[19] See Banz (1981), Basu (1983), Jegadeesh and Titman (1993), Cooper, Gulen, and Schill (2008), Novy-Marx (2013), and Ang, Hodrick, Xing, and Zhang (2006), respectively.

[20] The insignificant coefficient on stock return runup reflects the sample period and is not driven by the inclusion of β^{LCT} in the regression. In particular, when 2009, the year of the dramatic momentum crash (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016) is excluded from the sample, the t-statistic on return runup exceeds 4.0.

Table 9
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 β^{LCT} on innovations in leverage constraint tightness computed as of month t, the log of market equity, the log of the ratio of book equity to market equity, the gross profits-to-assets ratio, the year-over-year asset growth rate, the stock return during the 11-month period ending in $t-1$, return reversal computed as month t stock return, and idiosyncratic volatility computed as residual standard deviation from month t three-factor regressions on daily data. 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). All independent variables are normalized to have cross-sectional standard deviation of one. Reported are the average coefficients and the corresponding Newey and West (1987) t-statistics. The sample period is 1981 to 2014.

Variable	(1)	(2)	(3)	(4)	(5)
β^{LCT}	−0.13	−0.11	−0.11	−0.09	−0.08
	[−2.86]	[−2.57]	[−2.50]	[−2.32]	[−2.29]
Log market equity		−0.29	−0.27	−0.22	−0.24
		[−2.64]	[−2.45]	[−2.16]	[−3.34]
Log book-to-market ratio		0.29	0.27	0.29	0.27
		[3.30]	[3.11]	[3.44]	[3.62]
Gross profits-to-assets			0.19	0.20	0.19
			[4.44]	[4.36]	[4.22]
Asset growth			−0.190	−0.19	−0.19
			[−6.06]	[−6.06]	[−5.97]
Stock return runup				0.140	0.14
				[1.47]	[1.60]
Reversals				−0.79	−0.83
				[−10.23]	[−11.3]
Idiosyncratic volatility					−1.76
					[−1.49]

sidered predictors. The strong negative link between mutual funds' return sensitivity to changes in the tightness of leverage constraints and future performance is thus directly inherited from the stocks they hold.

7. 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 funds' stock holdings. The underlying intuition is that as the desire to take leverage increases, mutual funds, which face significant leverage restrictions, take advantage of the implicit leverage embedded in high-beta securities. Our measure captures the desire for leverage and reveals the tightness of leverage constraints, whereas existing proxies 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 5% annually. This finding is robust to adjusting for commonly used risk factors, controlling for fund characteristics, and varying portfolio formation approaches.

We show in portfolio sorts and Fama and MacBeth (1973) regressions that LCT is also 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. As a result, mutual funds that tilt their portfolios towards stocks with low LCT loadings are exposed to leverage constraint tightness risk and earn high future returns.

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