TWO ESSAYS ON MUTUAL FUND PERFORMANCE

A Dissertation

Presented to

The Faculty of the Graduate School

At the University of Missouri

In Partial Fulfillment

Of the Requirements for the Degree

Doctorate of Philosophy

By

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MAY 2012

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TWO ESSAYS ON MUTUAL FUND PERFORMANCE

Presented by Andrew A. Lynch

A candidate for the degree of

Doctorate of Philosophy

And hereby certify that, in their opinion, it is worthy of acceptance.

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I wish to dedicate my dissertation to JoBeth, for her unconditional love and support, and to my parents and grandparents, for instilling in me a love of learning.

ACKNOWLEDGEMENTS

I want to sincerely thank both the members of my committee and the faculty in the Department of Finance for their unwavering guidance and support of my research.

I am especially grateful to Dr. Sterling Yan. Not only for help on this dissertation, but for being an excellent mentor and teaching me the value of careful, methodical research.

I also wish to thank Dr. Dan French, Dr. John Howe, Dr. Grace Hao, Dr. J. Isaac Miller and Dr. Steve Ferris, for their feedback on this dissertation and their phenomenal support during my time in the doctoral program.

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ABSTRACT

In these two essays, I examine the relation between mutual fund characteristics and fund performance. In the first essay, I test the impact of liquidity and liquidity risk on mutual fund returns. I find that equity funds with the most illiquid holdings outperform those with the most liquid holdings by as much as 4.40 percent annually. Funds with high liquidity beta only marginally outperform those with low liquidity beta on average. However, this outperformance is significantly stronger after excluding periods of extreme market illiquidity. A one standard deviation increase in liquidity beta is associated with an increase in annualized returns of as much as 2.04 percent. Testing the liquidity and liquidity risk effects jointly reveals that both independently influence fund returns. Overall, I find that both the liquidity level and the liquidity risk of fund holdings are important determinants of mutual fund returns.

In the second essay, I test the relation between fund fees and fund performance. Theory suggests that mutual fund fees should be positively related to before-fee returns (Berk and Green (2004)), while recent empirical work documents a negative relation (Gil-Bazo and Ruiz-Verdu (2009)). I find that the previously identified negative relation is not robust to alternative empirical specifications. Portfolio sorting and regression analysis with controls for fund characteristics find a positive relation between before-fee returns and expense ratios. I also find a positive relation between before-fee returns and management fees, the fee used to compensate fund managers. Extending the analysis to proxies for manager skill, I find a positive relation between fees and both trading skill

and active share of holdings. Overall, there is substantial evidence of a positive relationship between the price of active fund management and performance.

CHAPTER 1

Liquidity, Liquidity Risk, and the Cross Section of Mutual Fund Returns

1. Introduction

The liquidity characteristics of assets pervasively affect their returns. Theory predicts a positive relation between illiquidity and required rates of return, as illiquid assets must offer a higher expected return than their liquid counterparts to attract investors (Amihud and Mendelson (1986)). Moreover, since liquidity systematically varies over time (Chorida, Roll, and Subrahmanyam (2000, 2001)) theory also suggests liquidity risk should be priced (Acharya and Pedersen (2005)). There is considerable empirical support for a liquidity premium (Brennan and Subrahmanyam (1996), Amihud (2002), and Hasbrouck (2009)) and moderate evidence of a liquidity risk premium (Pastor and Stambaugh (2003) and Watanabe and Watanabe (2008)) in equity returns.[1]

In this paper I test for the existence of liquidity and liquidity risk premia in equity mutual fund returns. Specifically, I address the following four research questions. First, do funds with less liquid holdings outperform those with more liquid holdings? Given the strong evidence of a liquidity premium in equity returns, the expectation is that illiquid funds will outperform liquid funds. However, the substantial transaction costs associated with trading illiquid equities may depress the returns of illiquid funds, weakening or eliminating the liquidity premium in fund returns. Second, does exposure to liquidity risk

[1] Pastor and Stambaugh (2003), Sadka (2006) and Korajczyk and Sadka (2008) find evidence that liquidity risk is priced in equities. However, several studies find different results. Acharya and Pedersen (2005) find little evidence of a liquidity risk premium and Hasbrouck (2009) finds no evidence. Watanabe and Watanabe (2008) find that only liquidity betas calculated during a high liquidity beta regime (approximately 10 percent of the sample) are priced in the cross section of stock returns.

positively impact mutual fund returns? To the extent that liquidity risk is priced in equities, I expect it to also impact fund returns. Third, do liquidity and liquidity risk effects in fund returns vary with the state of market liquidity? Recent research suggests both liquidity and liquidity risk premia will shrink and possibly invert during liquidity crises (Brunnermeier and Petersen (2009), Jensen and Moorman (2011)). Therefore, there might be stronger evidence of liquidity and liquidity risk premia after excluding periods of extreme market illiquidity. Finally, what is the relative importance of the liquidity and liquidity risk effects in fund returns? Current research suggests that the liquidity and liquidity risk premia are related. It is possible that the liquidity effect is subsumed by the liquidity risk effect (Watanabe and Watanabe (2008)), the liquidity effect dominates the liquidity risk effect (Acharya and Pedersen (2005)), or both independently impact returns (Korajczyk and Sadka (2008)).

It is important to examine the liquidity and liquidity risk premia in mutual fund returns for several reasons. First, as managed portfolios, mutual funds are an interesting laboratory for examining asset pricing phenomena such as the liquidity and liquidity risk effects. Second, with nearly $12 trillion dollars in assets managed at the end of 2010, U.S. mutual funds own a large percentage of U.S. financial assets and their performance directly impacts 90 million American investors.[2] Finally, an important function of mutual funds is to provide liquidity to investors through daily purchases and redemptions. While funds have an incentive to hold illiquid stocks in order to capture higher expected returns, they also have a conflicting incentive to hold stocks which are liquid or have minimal

[2] Investment Company Factbook (2011).

exposure to liquidity risk to minimize the costs associated with providing liquidity to shareholders (Edelen (1999) and Alexander, Cici and Gibson (2007)).[3] These competing incentives create uncertainty about the extent to which liquidity and liquidity risk will impact fund returns.

I begin this study by examining the liquidity premium. First, I confirm the existence of a liquidity premium in equity returns during my sample period of 1984 through 2008. For example, regressions reveal that a one standard deviation increase in a stock's Amihud illiquidity measure is associated with an increase in raw (risk-adjusted) annualized return of 3.96 (4.20) percent over the following year. Second, I investigate the existence of a liquidity premium in fund returns, measuring fund liquidity as the mean liquidity of fund stock holdings. A standard deviation increase in a fund's Amihud measure is associated with an increase in raw (risk-adjusted) annualized net fund return of 0.60 (0.72) percent. The relation is stronger in gross fund returns with a 0.84 (1.08) percent increase in returns.[4]

The finding that the liquidity premium is smaller in mutual fund returns than in equity returns is not surprising. First, diversified and overlapping fund holdings narrow the cross-sectional distribution of both returns and liquidity across mutual funds compared to equities. Second, funds generally avoid holding the smallest and most illiquid stocks to minimize the costs associated with portfolio rebalancing and liquidity

[3] Funds with illiquid assets will incur larger transaction costs in the presence of fund flows than those with more liquid assets, incentivizing managers to hold more liquid assets (Huang (2010)). Also, as fund outflows often coincide with liquidity crises (Acharya and Pedersen (2005)) funds with assets exposed to liquidity risk will see higher liquidity provision costs than funds with assets that are less exposed to liquidity risk.

[4] Gross fund returns are measured as net returns plus one-twelfth the annual expense ratio plus estimated transaction costs, estimated from changes in holdings as in Wermers (2000) and Kacperczyk, Sialm and Zheng (2008).

provision (Huang (2010)). This creates an even narrower cross-sectional distribution in fund liquidity than in equity liquidity. In spite of this relatively narrow dispersion in fund liquidity and fund returns I find evidence of a statistically and economically significant liquidity premium in fund returns.

I next examine the liquidity risk premium. Following prior literature, I define liquidity risk as the covariance of asset returns with changes in market liquidity (Pastor and Stambaugh (2003) and Sadka (2010)). I estimate liquidity betas from rolling regressions of returns on innovations in market liquidity.[5] A mutual fund's liquidity beta is measured either directly from regressions of fund returns on innovations in market liquidity ("fund liquidity betas") or as the mean liquidity betas of stocks held by the fund ("holdings liquidity betas"). Holdings liquidity betas are potentially superior measures of liquidity risk than fund liquidity betas for two reasons. First, because holdings liquidity betas do not require fund survivorship for any period of time they preserve young, often illiquid, funds in the sample. Second, stock-level betas aggregated to the fund portfolio level may be more precise than those estimated directly from mutual fund returns (Jiang, Yao and Yu (2007)).

I find a significant liquidity risk premium in equities during my sample period. Regressions show that a one standard deviation increase in liquidity beta is associated with an increase in risk-adjusted annualized return of up to 1.80 percent. The results are weaker in mutual funds. Using fund liquidity betas I find little evidence of a liquidity risk. Most coefficients are not statistically significant, while those that are significant

[5] Market liquidity is defined as in either Acharya and Pedersen (2005), Pastor and Stambaugh (2003), or Sadka (2006).

have opposite signs. A one standard deviation increase in Pastor-Stambaugh beta results in a decrease in annual returns of 0.36 percent while an increase in Sadka beta results in an increase in annual returns of 0.48 percent. However, using holdings liquidity betas to measure liquidity risk I find a consistently positive relation between liquidity risk and expected returns. For example, funds ranked in the top Sadka liquidity beta decile outperform funds in the bottom decile by a raw (risk-adjusted) annualized return of 3.48 (2.64) percent, which is both statistically and economically significant. Regressions reveal a uniformly positive relation between liquidity beta and fund returns, though many of the coefficients are not statistically significant. Overall, results based on holdings liquidity betas demonstrate a generally positive, albeit weak, relation between liquidity risk and fund returns.

My analysis up to this point has been unconditional. However, theory suggests that the liquidity and liquidity risk effects are time varying and dependent on market liquidity. Liquid stocks generally outperform illiquid stocks during liquidity crises, periods of time with significantly negative market liquidity shocks (Goyenko and Sarkissian (2008), Jensen and Moorman (2011)). Therefore, the liquidity premium is expected to invert during periods of high market illiquidity (Brunnermeier and Petersen (2009)). Turning to the liquidity risk premium, stocks with high positive liquidity betas will see negative returns during liquidity crises relative to stocks with low or negative liquidity betas (Vayanos (2004)). Therefore, negative liquidity shocks can weaken or even invert the liquidity risk premium (Acharya, Amihud and Bharath (2010)). It is possible both liquidity and liquidity risk premia exist in fund returns after excluding

periods of large negative aggregate liquidity shocks, but are weakened or obscured in unconditional analysis.[6]

I therefore introduce a liquidity crisis indicator variable into my regression analysis so that I can measure the liquidity and liquidity risk premia separately inside and outside of liquidity crises.[7] Excluding months of high aggregate illiquidity, a one standard deviation increase in a fund's Amihud measure predicts an increase in annualized risk-adjusted net fund returns of 0.48 percent, which is twice the size of the 0.24 percent unconditional liquidity premium. During liquidity crises the liquidity effect is negative. A one standard deviation increase in Amihud is associated with a decrease in annualized risk-adjusted net fund returns of 0.48 percent.

Turning to liquidity risk, a one standard deviation increase in holdings liquidity beta is associated with an increase in annualized risk-adjusted net and gross fund returns of as much as 0.96 percent after excluding liquidity crises. This finding is especially significant considering the largest unconditional liquidity risk premium found is 0.36 percent. Both Amihud and Pastor-Stambaugh liquidity betas show a statistically and economically significant positive relation with fund returns during non-liquidity crisis periods, though an increase in Sadka beta is associated with a statistically insignificant increase in annualized risk-adjusted returns of 0.48 percent. During liquidity crises the liquidity risk effect becomes a discount of as much as -1.44 percent on a risk-adjusted

[6] An illiquid asset requires a return premium, on average, to entice investor to hold the asset (Amihud and Mendelson (1986)). If illiquid assets earn abnormally negative returns during liquidity crises, then, in order to generate a liquidity premium on average, those same illiquid assets must earn a large premium during periods not in liquidity crises. A similar argument applies to a liquidity risk premium. Therefore, the fact that illiquid or high liquidity beta stocks outperform their liquid or lower beta counterparts in non-liquidity crisis periods is evidence which supports the existence of liquidity and liquidity risk premia.

[7] The top 20 percent most illiquid months of my sample are assigned to the illiquid regime. I define market illiquidity as innovations in aggregate normalized Amihud (Watanabe and Watanabe (2008)).

basis. Overall, I find that both the liquidity and liquidity risk premia are time varying, and failing to condition on this time variation can obscure their existence in fund returns. Excluding liquidity crises, both effects have a significant positive impact on mutual fund returns.

Liquidity and liquidity risk are closely related. Illiquid assets tend to be more sensitive to changes in market liquidity (Acharya and Pedersen (2005), Watanabe and Watanabe (2008)), implying the high expected returns of illiquid assets may be due, in part or in total, to liquidity risk. It is therefore important to test the two effects jointly in order to correctly measure the individual impact of each effect on fund returns. My final analysis considers both the liquidity and liquidity risk effects simultaneously in the presence of controls for liquidity crises. I find that liquidity and liquidity risk premia remain statistically and economically significant in fund returns when tested jointly. An increase in a fund's Amihud illiquidity measure predicts and increase in raw (risk-adjusted) fund returns of 1.32 (0.36) percent. A similar increase in Pastor and Stambaugh holdings liquidity beta results in an increase in raw (risk-adjusted) annualized fund return of 1.56 (0.84) percent. This evidence suggests liquidity and liquidity risk are separate effects which independently impact fund returns.

Overall, I draw several important conclusions from these results. First, both the liquidity level and liquidity risk of fund holdings impact fund returns, providing support for theories that both are priced. Second, both liquidity and liquidity risk premia vary significantly with market liquidity. This time variation is large for liquidity and critically important for liquidity risk. Failing to account for this variation obscures the effect

liquidity risk has on fund returns. Finally, tested jointly, liquidity and liquidity risk are separate effects which independently impact fund returns.

This paper is similar to, yet distinct from, Sadka (2010) and a concurrent paper by Dong, Feng, and Sadka (2011), which investigate the impact of liquidity risk on hedge fund and mutual fund returns respectively. Sadka (2010) focuses on hedge funds, which have different trading strategies and risk characteristics than mutual funds. Also, my use of equity mutual funds allows for analysis of both liquidity and liquidity risk using fund holdings, something that cannot be done in hedge funds. The primary distinction between my paper and Dong, Feng, and Sadka (2011) is my use of holdings to measure liquidity and liquidity betas. Multivariate regressions allow me to test the effects of liquidity and liquidity risk jointly, conditioned on aggregate liquidity, and with controls for fund characteristics that are known to impact fund returns.

The remainder of this paper is organized as follows. I outline data and methods in Section 2. Section 3 analyzes the liquidity premium and Section 4 analyzes the liquidity risk premium. Section 5 conducts a conditional analysis on both liquidity and liquidity risk effects while Section 6 looks at the two effects jointly. I conclude in Section 7.

2. Data and Methods

2.1. Sample Construction

To construct my sample I begin with all equity mutual funds listed in the CRSP Survivorship-Bias Free Mutual Fund Database between 1984 and 2008.[8] As in Yan (2008) all share classes of the same fund are aggregated to the fund level to provide one

[8] See Elton, Gruber and Blake (2001) and Fama and French (2010) for a discussion of the biases inherent in CRSP mutual fund returns prior to 1984.

observation for each mutual fund and then matched to the Thomson CDA/Spectrum holdings database using the MFLINKs file provided by the Wharton Research Database Service.[9] The holdings database imposes no minimum size or age requirements on funds for inclusion, and is therefore free of survivorship bias.[10] To avoid incubation bias I include funds only after their total net assets exceed 15 million dollars (Evans (2010)).[11] Price, return, and volume data are taken from the CRSP monthly stock file and used to calculate Amihud's illiquidity measure. Effective spreads are calculated from the Trade and Quote (TAQ) database for all equities reported in CRSP. Fund returns are measured either net, as reported in the CRSP Mutual Fund Database, or gross, defined as net returns plus one-twelfth the annual expense ratio and estimated monthly transaction costs, where transaction costs are estimated from changes in holdings as in Wermers (2000) and Kacperczyk, Sialm and Zheng (2008). For a more thorough discussion of my sample construction, please see Appendix 1.

As shown in Panel A of Table 1, my final mutual fund sample consists of 2,480 funds with 210,110 fund month observations. Panel B reports the summary statistics of fund characteristics.[12] Total Net Assets is the total assets managed by the fund. Total Family Assets is the sum of total net assets of all funds managed by that fund's management company. Age is measured as the number of years since the oldest fund

[9] Portfolio-level fund characteristics such as return, expense ratio, load and turnover are measured as the value weighted mean of fund share class characteristics, weighted by share class total net assets.

[10] See Wermers (2000) for a thorough discussion of the CDA/Spectrum holdings database.

[11] Analyses have been conducted using alternative cutoffs of 5 and 10 million dollars, and similar results are found.

[12] Reported summary statistics are the time series means of cross-sectional summary statistics.

share class was reported in the CRSP Mutual Fund Database. Flow is net asset flow, and is the percent change in total net assets not explained by fund returns. Max load is the larger of the front or rear end load. Cash is percent of total net assets held in cash. Expense ratio is the annual charge as a percentage of assets invested levied against fund shareholders. Turnover is the percent of fund assets traded annually, measured as the minimum of security sales and purchases divided by the 12-month average total net asset of the fund.

Fund and portfolio returns are risk adjusted using three models. All of my analyses present results using single-factor alphas (CAPM), three-factor alphas (Fama and French (1996)) and four-factor alphas (Carhart (1997)) as well as raw returns. For portfolio sorting analyses, alphas are estimated as the intercept from time series regressions of portfolio excess returns on the risk adjustment factors.

For regression analyses, alphas used as dependent variables are estimated through a rolling regression method similar to Carhart (1997). Every month I use the previous 60 months of returns to estimate factor betas (a minimum 48 months of non-missing returns is required). Alphas are defined as the difference between realized returns and expected returns based on the estimated factor loadings.[13]

2.2. Liquidity Level

I employ two measures of liquidity; the Amihud price impact measure and effective spread. Amihud is calculated as in Amihud (2002) as the monthly equal weighted mean of daily price impact for all equities in CRSP:

[13] I have also run these analyses using alphas from 36 month and 48 month rolling regressions and find qualitatively similar results.

$$Amihud_{i,t} = \frac{1}{n}\sum_{d=1}^{n}\frac{|ret_{i,d,t}|}{dvol_{i,d,t}} \quad (1)$$

where $ret_{i,d,t}$ is the return on day d in month t for stock i, $dvol_{i,d,t}$ is the daily dollar volume of stock i (in millions) and n is the number of days in month t that the stock has at least one transaction. Small stocks with infrequent trading often have extremely large *Amihud* values. Following Watanabe and Watanabe (2008), I minimize their impact on my analysis by discarding the *Amihud* values for stocks with less than 15 trading days in a month.[14] As a ratio of absolute return to dollar volume, *Amihud* gauges how sensitive a stock's return is to trading. Large returns associated with low dollar volume suggest low liquidity. Small returns associated with high dollar volume suggest high liquidity. Therefore, *Amihud* is decreasing in liquidity.

I also use effective spread to measure liquidity (Chordia, Roll and Subrahmanyam (2000), Goyenko, Holden and Trizcinka (2009)). I calculate monthly equity effective spreads as the dollar volume mean of transaction log effective spreads during each month for 1993 through 2008:

$$ESpread_{i,t} = \frac{1}{\sum_{\tau=1}^{n} dvol_{i,\tau,t}}\sum_{\tau=1}^{n}\left(dvol_{i,\tau,t} * 2 * \left|ln\left(P_{i,\tau,t}\right) - ln\left(M_{i,\tau,t}\right)\right|\right) \quad (2)$$

where $dvol_{i,\tau.t}$ is the dollar volume, $P_{i,\tau,t}$ is the price and $M_{i,\tau,t}$ is the quoted spread midpoint for transaction τ of stock i, and n is the number of transactions in month t.[15] As

[14] As stocks with fewer than 15 trading days also have small market capitalizations, they make up a very small percentage of mutual fund assets (Daniel et al. (1997)). Therefore, this 15 day cutoff has a small impact on my results. Alternate cutoffs of 5 and 10 days produce qualitatively similar results for mutual fund analyses.

[15] Following Chorida, Roll and Subrahmanyam (2002) I remove transactions with the following attributes: quotes with negative spreads or depth, quotes with spread greater than 4 dollars or 20 percent the midpoint, trades with negative prices, trades out of sequence and trades occurring outside times the market is open.

effective spread increases investors incur higher costs to trade, reducing the liquidity of the stock. Therefore, as with *Amihud*, *ESpread* is inversely related with liquidity.

I measure a fund's liquidity as the dollar holdings weighted mean of their equity holding's liquidity measures.[16] While there are many empirical proxies for liquidity, they all measure either the direct or the indirect cost of trading (Hasbrouck (2009)). As *ESpread* is an often used measure of direct trading costs (Chordia, Roll, and Subramanyam (2000)) and the *Amihud* price impact measure is often used for indirect trading costs (Hasbrouck (2009)), I believe my use of these two proxies is appropriate for examining the liquidity premium.[17] Alternatively, Huang (2010) measures fund liquidity as percent of holdings in the bottom 1, 2 or 5 percent *Amihud* percentile. While this proxy is informative, a weighted average of holdings *Amihud* is a better proxy of liquidity for asset pricing tests. I will note, though, that my results are robust to several other proxies of liquidity.[18]

2.3. Liquidity Risk

Following Pastor and Stambaugh (2003) I define liquidity risk as the covariance of returns with innovations in aggregate liquidity. I utilize three generally accepted proxies of aggregate liquidity used in the liquidity risk literature. First, I measure

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[16] Massa and Phalippou (2005) measure fund liquidity in a similar manner, though they use a normalized *Amihud* measure (Acharya and Pedersen (2005)).

[17] Examining the liquidity premium in fund returns, Yan (2008) also uses two proxies: a price impact measure and a spread measure.

[18] Results are qualitatively similar using other high frequency measures, such as quoted spread or a measure based on Kyle's lambda (Hasbrouck (2010)), or other low frequency measures such as the Roll measure (Roll (1984)), the Pasture and Stambaugh measure (Pastor and Stambaugh (2003)) or Gibbs measure (Hasbrouck (2010)).

aggregate liquidity from the equal weighted mean of normalized *Amihud* across all common stocks (Acharya and Pedersen (2005)). Normalized *Amihud* is defined as:

$$AmihudN_{i,t} = min\left(0.25 + 0.30Amihud_{i,t}P_{M,t-1}, 30.00\right) \quad (3)$$

where $Amihud_{i,t}$ is stock *i*'s *Amihud* measure as defined in equation (1) and $P_{M,t-1}$ is an adjustment factor, defined as the ratio of total market capitalization in month *t-1* to total market capitalization in July 1962.[19] Monthly market liquidity is then calculated as the equal weighted mean of the liquidity of all common stocks with at least 15 trading days per month and prices between 5 and 1000 dollars at the end of the previous year (Watanabe and Watanabe (2008)). Innovations in market *AmihudN* are defined as the negative residuals from an AR(2) process.[20]

Second, I use the Pastor-Stambaugh aggregate liquidity measure provided by WRDS. Pastor and Stambaugh (2003) measure liquidity as the coefficient from a regression of daily stock returns on the prior day's stock return and signed dollar volume. If signed dollar volume is positively related with the following day's return then price movements are sustained, suggesting they were the result of informed trading. If signed dollar volume is negatively related with the following day's return then price movements are being reversed, suggesting they were the result of illiquidity. The more negative the coefficient, the more illiquid the stock. The more positive the coefficient, the more liquid the stock. They then aggregate this measure across all common equity with prices

[19] For a discussion of how this function normalizes the distribution of the *Amihud* measure, see Acharya and Pedersen (2005).

[20] Multiplying the AR(2) residuals by negative one is done to convert *AmihudN* from a measure of illiquidity into a measure of liquidity. Also, an AR(2) process is sufficient to make *AmihudN* stationary.

between 5 and 1000 dollars. Innovations in aggregate liquidity are then measured as the unexpected changes in the first difference of aggregate liquidity.

Third, I use the market liquidity measure proposed by Sadka (2006) and provided by WRDS. Constructed from transaction level data from 1983 through 2008, using ISSM and TAQ, Sadka (2006) estimates four price impact components (permanent fixed, transitory fixed, permanent variable and transitory variable). As Sadka (2006) finds only the permanent variable component is priced in equities, the Sadka market liquidity measure is calculated as the equal weighted mean of the permanent variable component. As in Sadka (2010), innovations in market liquidity are defined as the negative residuals from an AR(3) process.

I estimate equity liquidity betas from rolling regressions as in Sadka (2010). Time-varying betas are measured as the β_L regression coefficient from the following model:

$$RETRF_{i,t} = \alpha_{i,k} + \beta_{i,k,L} LiqInnov_t + \beta_{i,k,M} MKTRF_t + \beta_{i,k,S} SMB_t + \beta_{i,k,H} HML_t + \beta_{i,k,U} UMD_t + \varepsilon_{i.k} \quad (4)$$

where $RETRF_{i,t}$ is stock return in excess of the risk free rate, $LiqInnov_t$ is the innovation in market liquidity (measured by either *Amihud*, *PS* or *Sadka*), and $MKRTF_t$, SMB_t, HML_t, UMD_t are the traditional measures from the four-factor model (Fama and French

(1996), Carhart (1997)).[21] The liquidity beta in month k, $\beta_{i,k,L}$, is calculated using the prior 60 months (minimum 48 months)[22] of returns.[23]

Liquidity betas for funds are estimated in two ways. For the first method I use equation (4), regressing fund excess net returns on innovations in market liquidity ("fund liquidity betas"). For the second method I measure fund liquidity betas as the dollar value weighted mean of the liquidity betas of stock holdings ("holdings liquidity betas"). While I use both betas in my initial liquidity risk tests, there are two reasons to expect holdings liquidity betas to be superior proxies of liquidity risk in asset pricing tests to fund liquidity betas. First, the requirement of at least 48 months of returns to generate fund liquidity betas removes funds from my analysis during their earliest years. Rolling regressions also impose survivorship bias into the analysis, as funds with less than four years of returns will never enter the analysis. Holdings liquidity betas do not suffer from this problem, as I am able to assign betas to funds the first month they enter the sample.[24] Second, stock betas aggregated to the fund portfolio level may be more precise than those generated directly from mutual fund returns (Jiang, Yao and Yu (2007)).

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[21] MKTRF, SMB, HML and UMD factors are provided by the Wharton Research Database Service. MKTF, SMB and HML can be directed downloaded from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_bench_factor.html

[22] I require a minimum 48 months of non-missing return observations during that 60 month window. Since the Sadka market liquidity measure is only available starting in 1983, and I require a minimum 48 months of returns to generate betas, the sample of Sadka betas spans 1987 through 2008 unlike the AmihudN and PS betas which span 1984 through 2008.

[23] These analyses have been replicated using liquidity betas generated from a model including only the market risk premium (as in Watanabe and Watanabe (2008) and Sadka (2010)) and produce qualitatively similar results.

[24] I am able to assign holdings liquidity betas to each of the 210,110 fund observations in my sample, but only 142,721 observations using fund liquidity betas.

3. Liquidity Premium

While there is considerable research suggesting liquidity is priced in equities, current evidence is mixed concerning the relation between liquidity and fund returns. Massa and Phalippou (2005) and Yan (2008) find evidence of a liquidity premium conditioned on high market liquidity and small fund size, respectively, while Khandani and Lo (2009) finds no evidence for the premium utilizing a return auto-correlation proxy of fund liquidity. I first confirm the liquidity premium in equities during my sample period and then examine whether a cross-sectional dispersion in fund holdings liquidity results in a fund level liquidity premium.

Table 2 reports analysis based on all common stocks in CRSP with monthly share prices in excess of one dollar. In Panel A I sort equities at the end of every December into decile portfolios by their mean *Amihud* during that year and hold those portfolios for the following year. The table reports the equal weighted mean monthly liquidity measures and realized returns for these portfolios. I find a very large dispersion in liquidity across stocks. Specifically, there is a 4.10 percent difference in effective spread between the top and bottom portfolios.

Looking at portfolio returns in Panel A reveals two important results. First, the liquidity premium is economically large. The four factor alpha of the difference in returns between the tenth and the first decile portfolio is 94 basis points per month for *Amihud* portfolios and 95 basis points for effective spread portfolios. Second, the liquidity premium is not driven solely by the extreme portfolios. The four factor alpha of the difference between the ninth and second decile portfolios is 37 basis points for *Amihud* portfolios and 38 basis points for effective spread portfolios.

Panel B of Table 2 tests the impact of liquidity on equity returns with regressions using the same sample as Panel A. Excess and risk-adjusted stock returns are regressed on lagged annual mean illiquidity standardized with a mean of zero and a unit standard deviation, utilizing both Fama-MacBeth regressions and pooled OLS. [25] The results align with the portfolio sorting analysis, showing liquidity has a large effect on returns. A one standard deviation increase in *Amihud* (effective spread) is associated with an increase in expected returns of as much as 37 (38) basis points per month. The economic magnitude of these results is large and in line with those in similar studies (Brennan, Chordia and Subrahmanyam (1998), Amihud (2002), Goyenko, Holden and Trzcinka (2009)). [26]

I next examine mutual fund liquidity. Panel A of Table 3 reports fund characteristics sorted by fund *Amihud* measure. As expected, I find strong correlation between liquidity and several fund attributes. Funds with less liquid holdings (higher mean *Amihud* illiquidity ratio) hold more cash, have smaller total assets, have larger cash inflows, are younger and charge higher expenses but lower loads.[27] An intriguing finding is the lack of positive correlation between holdings illiquidity and fund turnover ratio. What is important to learn from Panel A is that, as many of these characteristics are known to impact fund returns (Chen, Hong, Huang and Kubik (2004)), it may be

[25] Standard errors for panel regressions are clustered by time (monthly) and firm (Pedersen (2009)).

[26] When, as in other studies, traditional asset pricing control variables are included (i.e. logged market capitalization, book-to-market ratio, return standard deviation and lagged returns) the magnitude of the liquidity premium I find is very similar to those studies. As my primary concern here is with fund illiquidity, and the implications of including different control variables for equity regressions than fund regressions uncertainly alters comparative interpretations, I choose to report only univariate results.

[27] All differences between top and bottom portfolios are statistically significant at the 1 percent level.

important to control for these fund characteristics with a multivariate analysis to accurately test the liquidity premium.

Panels B and C of Table 3 report the equal weighted liquidity measures and returns (both net and gross) of fund illiquidity decile portfolios. I find the cross-sectional dispersion in liquidity across funds is much smaller than that across equities. While in equities there is a difference of 8.636 between the top and bottom *Amihud* deciles, the difference between top and bottom fund *Amihud* deciles is only 0.262. This is not surprising. As in Daniel et al. (1997), the average stock held by funds in my sample is in the fourth largest size quintile. Since liquidity is highly positively correlated with market capitalization it is not surprising that funds hold stocks that are, on average, very liquid.[28] The total dispersion of fund *Amihud* (0.001 to 0.263) is roughly equivalent to the change in *Amihud* the bottom and fifth equity illiquidity decile (0.002 to 0.264). Note that in equities the cross-sectional liquidity premium between the first and fifth deciles is small (negative) looking at raw (risk-adjusted) returns. This suggests the expected liquidity premium in fund returns, if it exists, will be less than that found in equities.

The difference in net fund returns between the highest and lowest illiquidity deciles is not statistically different for either *Amihud* or effective spread portfolios. However, looking at gross returns, there is a strong economic and statistical difference of 29 (15) basis points in raw (risk-adjusted) gross returns per month between top and bottom *Amihud* portfolios. While the difference in returns for effective spreads is not statistically significant they are still a positive and economically large 37 (10) basis

[28] Huang (2010) finds, on average, funds have 18.44 percent of their holdings in the lowest *Amihud* percentile.

points per month. These portfolio sorting results suggest the liquidity premium impacts gross fund returns, but not net fund returns. This difference in results between net and gross returns implies transaction costs reduce the size of the premium and funds capture some of the premium through expense ratios.

I next employ multivariate regressions which control for other fund characteristics. Panel D reports Fama-MacBeth and pooled OLS regressions (with standard errors clustered by time and fund) of excess and risk adjusted fund returns on lagged standardized annual mean liquidity, total net assets, family total net assets, asset flow, age, expense ratio, turnover, and maximum load.[29] For the sake of brevity, the coefficients on the control variables are not reported. Fama-MacBeth regressions reveal a strong positive relation between *Amihud* and risk adjusted returns. A one standard deviation increase in *Amihud* predicts a net (gross) increase in four factor alphas of 6 (9) basis points per month over the following year. When using effective spread, however, the relation is only statistically significant for gross returns. Pooled OLS produces slightly different results, suggesting that only raw and CAPM adjusted returns are related to either fund *Amihud* or effective spreads.

Overall, I take the evidence presented in Tables 2 and 3 to suggest the liquidity of holdings impacts fund returns. The discrepancy between gross and net returns reveals that trading costs have a substantial negative impact on returns to holding illiquid equities, and some of the remaining liquidity premium is captured by managers through expenses.

[29] For a discussion of why inclusion of these fund characteristics is important in fund performance studies, see Chen, Hong, Huang and Kubik (2004)).

However, cross-sectional regressions imply that *Amihud* positively impacts both net and gross returns.

4. Liquidity Risk Premium

I start my analysis of the liquidity risk premium in Table 4 by examining the effect of liquidity risk on equity returns. In Panel A I sort equities every month into decile portfolios by liquidity betas calculated using rolling regressions as outlined in Equation (4).[30] The difference in returns between the top and bottom liquidity beta deciles is positive for all three liquidity beta measures, though only statistically significant for *Amihud* betas. The top *Amihud* beta decile outperforms the bottom decile by 43 basis points per month on a risk-adjusted basis. Regressions of excess and risk-adjusted equity returns on cross-sectionally standardized liquidity betas, reported in Panel B, reveal a statistically and economically strong relation. Looking at four-factor alphas, an increase in any of the three liquidity betas predicts an increase in the following month's risk-adjusted return of at least 14 basis points (using either Fama-MacBeth or pooled OLS).

As discussed in Section 2.3, I calculate liquidity betas for funds using two different methods. The first is rolling regressions of fund excess returns on innovations in market liquidity and the four risk factors used in Carhart (1997), as shown in Equation (4). I refer to the betas estimated in this way as fund liquidity betas. The second method is a two-step procedure. I calculate rolling betas for all equities using Equation (4) and then measure the liquidity beta of a fund as the dollar holdings weighted mean liquidity beta of fund stock holdings. I refer to theses as holdings liquidity betas.

[30] Monthly rebalancing of portfolios is done to match prior liquidity risk research such as Sadka (2010).

Table 5 reports the time series means of cross-sectional summary statistics of holdings liquidity betas (HBeta), fund liquidity betas (FBeta) and the pairwise absolute difference between the two (|H-F|). Before addressing the difference in the two liquidity risk methods, I point out the near symmetry of liquidity betas around zero. Similar to Watanabe and Watanabe (2008), I find that while equity liquidity betas are positive on average the 20 to 30 percent most liquid equities have negative liquidity betas.[31] Since funds invest in mostly large, highly liquid stocks it is not surprising to find slightly over half of equity funds have negative liquidity betas.

Comparing holdings liquidity betas to fund liquidity betas, there are two relevant differences. The first is that holdings betas have a larger cross-sectional dispersion than fund betas. As holdings betas can be calculated for funds the first month they enter the sample, a portion of this increased dispersion may be explained by being able to estimate a HBeta for young, small funds that are most likely more concerned with liquidity risk for which an FBeta cannot be estimated.[32] The second difference is that the two methods estimate different betas for many of the same fund observations. The variable |H-F| is measured as the pairwise absolute difference between HBeta and FBeta. This variable demonstrates that while some funds are assigned economically similar betas (the 10th percentile *Amihud* absolute difference is only 0.002) the difference for some funds is very large. For instance, considering *Amihud* betas, the 99th percentile value of |H-F| is 0.072.

[31] In untabulated results I find results similar to Watanabe and Watanabe (2008) using equities during my sample period; that only the most liquid stocks have negative liquidity betas.

[32] However, this difference between fund and holdings liquidity betas remains after lowering the rolling window from 60 months to 12 (Sadka (2010)). At 12 months most fund observations can be assigned fund betas. The difference in betas is, therefore, not due solely to differing samples.

The increase in FBeta from the 1st percentile to the 99th percentile is 0.093. Choosing HBeta over FBeta (or vice-versa) effectively moves some funds from the bottom liquidity risk decile to the top. This large absolute difference exists for *PS* and *Sadka* betas as well. While these results do not necessarily provide insight into which measure of fund liquidity risk is more accurate, they do show there are substantial differences in the two measures both for the entire sample and on a fund level basis.

Table 6 applies the same analysis as in Table 4 to fund liquidity risk, though in this case I conduct portfolio sorting and regressions using both fund liquidity betas (Panels A and B) and holdings liquidity betas (Panels C and D). While fund betas and holdings betas are different, analyzing the relation between both betas and expected returns provides insight into which might more accurately proxies for fund liquidity risk.[33] Starting with fund liquidity betas, portfolio sorting in Panel A reveals a mixed relation between betas and expected returns. In 6 out of 12 return series the top beta decile underperforms the bottom decile. The only statistically significant difference, three-factor adjusted returns to *Pastor-Stambaugh* beta sorted portfolios, is a negative 16 basis points per month, which does not suggest a liquidity risk premium. Regression results reported in Panel B are no more coherent. While many of the coefficients show a positive relation between liquidity betas and expected returns, there are still several which are negative. Pooled OLS finds a one standard deviation increase in Sadka beta

[33] Admittedly, this analysis suffers from a joint hypothesis problem. If a liquidity beta measure is not related to asset returns, that does not inherently mean it does not proxy for liquidity risk. It is possible liquidity risk is not priced, hence no relation between beta and returns. However, the alternate situation is not inherently true. Current asset pricing theory does not provide for explanations of how a liquidity beta measure could be related to expected returns without being a proxy for liquidity risk. I therefore posit that if one type of liquidity beta is positively related to returns while the other is not, then the beta related to returns is the better proxy for liquidity risk.

predicts a 4 basis point increase in four factor alphas. However, Fama-MacBeth regressions find a -3 basis point change in returns for an increase in *Pastor-Stambaugh* beta.

I next look at holdings liquidity betas. The relation between holdings liquidity beta and returns is not as strong as that found between equity liquidity betas and returns. However, unlike the fund liquidity beta analysis, these results support a liquidity risk premium. Portfolio sorting, reported in Panel C, shows 11 out of 12 top minus bottom beta portfolio return differences are positive, 5 statistically so. Top decile *Sadka* beta funds outperform the bottom decile funds by a raw (risk-adjusted) 29 (22) basis points per month. The regression results in Panel D are not as strong, but are uniformly positive. A one standard deviation increase in *Sadka* beta predicts a raw (single factor adjusted) return increase of 6 (7) basis points.

This evidence is consistent with a liquidity risk premium in mutual fund returns, though it is not overwhelming. These results do reveal, however, that holdings liquidity betas show a relation to expected returns that is much more in line with asset pricing theory than fund liquidity betas. As this relation is more in line with liquidity risk being priced, I use holdings liquidity betas for the remainder of this study.

5. Conditional Analysis

5.1. Motivation

All the analyses up to this point have been unconditional. However, there are strong reasons to believe the liquidity and liquidity risk premia are time varying and dependent on market liquidity. Liquid stocks tend to perform well during negative market

liquidity shocks relative to their illiquid counterparts (Goyenko and Sarkissian (2008), Jensen and Moorman (2011)). Therefore, the expected liquidity premium can weaken or even reverse (a liquidity discount) during periods of high market illiquidity (Brunnermeier and Pedersen (2009)). Similarly, for the liquidity risk premium, stocks with high positive liquidity betas will see large contemporaneous negative returns during liquidity crises while stocks with low or negative betas will see zero or positive abnormal returns (Vayanos (2004)). Therefore, during such liquidity crises the liquidity risk premium may invert (Acharya, Amihud and Bharath (2010)).

The effect of liquidity crises on the liquidity and liquidity risk premia is especially severe for mutual funds, as their holding period is exogenously determined. Forced asset sales due to cash outflows that are correlated with liquidity crises (Acharya and Pedersen (2005)) will exacerbate liquidity provision costs for funds with illiquid holdings (Alexander, Cici and Gibson (2007)). For both liquidity and liquidity risk premia, it is possible that they conditionally exist in fund returns during periods which do not have high market illiquidity, but are obscured or weakened unconditionally due to liquidity crises.

I create a liquidity crisis indicator variable equal to one for all months with aggregate *Amihud* innovations in the highest quintile[34] of my sample period.[35] Figure 1 shows a line graph of the innovations in aggregate *Amihud* with a horizontal line at 0.142, representing the 80th percentile of innovations. The dark gray shaded regions represent

[34] I have also conducted these analyses with the high liquidity regime defined as the top decile of aggregate *Amihud* innovations, and have found similar results.

[35] This is not to be confused with the high liquidity beta state used by Watanabe and Watanabe (2008). While there may be some correlation between negative aggregate liquidity shocks and high liquidity betas, I am concerned with these shocks immediate impact on returns, not on betas.

months traditionally considered by the literature as liquidity crises (i.e. October 1987) and light gray shaded regions represent months which have been classified by the NBER as in recession. While this indicator variable does not perfectly align with all of these events, it captures a large majority of them while also identifying intermediate months with severe negative liquidity shocks (Watanabe and Watanabe (2008)).

5.2. Conditional Liquidity Premium

I find strong evidence for a time varying liquidity premium. Excluding high aggregate illiquidity months, a one standard deviation increase in *Amihud* (effective spread) predicts an increase in raw net returns of 120 (288) basis points per year. An increase in *Amihud* results in a statistically significant increase in annualized net and gross risk-adjusted returns of 48 basis points. Another important result of this analysis is that the difference in coefficient magnitude between net and gross returns is small, implying that fund managers pass on to investors almost the entire conditional liquidity premium they earn (even when accounting for trading costs).

Interestingly, I also find evidence for a flight-to-liquidity effect in fund returns. A liquidity premium exists in fund returns outside of liquidity crises and a liquidity discount exists during liquidity crises. Combining the liquidity effect with the marginal effect measured during crises, a one standard deviation increase in *Amihud* predicts a decrease of 12 (48) basis points annually in raw (risk-adjusted) net returns during liquidity crises.[36] While this effect may be attributable to many phenomena, it supports a theory where investors transfer assets from illiquid to liquid stocks during liquidity crises, which puts

[36] The joint test of the liquidity effect with the interaction produces a statistically significant risk-adjusted annualized -48 basis points with a *p*-value of 0.03.

an upward pressure on liquid stock prices and a downward pressure on illiquid stock prices. During liquidity crises the liquidity premium not only weakens but inverts.

5.3. Conditional Liquidity Risk Premium

Excluding liquidity crises, I find evidence of a significant liquidity risk premium in mutual fund returns. Table 8 reports the coefficients from regressions of excess and abnormal fund returns on cross-sectionally standardized liquidity betas, a liquidity crisis indicator variable, and their interaction (control variables are included but coefficients are not reported). I find *Amihud* and *Pastor-Stambaugh* liquidity betas have a significant positive relation with future net and gross fund returns.[37] A one standard deviation increase in *Pastor-Stambaugh* liquidity beta predicts an increase in raw (risk-adjusted) annualized returns of 156 (84) basis points while an increase in *Amihud* betas results in an increase in net (gross) risk-adjusted returns of 84 (96) basis points.

I also find that the liquidity risk premium inverts during liquidity crises. The negative risk and return relation during negative liquidity shocks is several times larger in absolute value than the positive relation during non-liquidity crisis periods. A one standard deviation increase in *Amihud* beta decreases expected risk-adjusted net return by an annualized 252 basis points during the illiquid regime, three times the 84 basis point increase predicted outside the regime (a net decrease in expected returns of 168 basis points, statistically significant with a *p*-value of 0.04). These results not only explain the weakly positive unconditional liquidity risk relation to expected returns shown in Table

[37] I have run this analysis using fund liquidity betas instead of holdings liquidity betas and find results consistent with those of Table 6. Fund liquidity betas during non-liquidity crisis periods show mixed results; sometimes positive and sometimes negative.

6, but also provide additional evidence of the flight-to-liquidity effect and how it impacts portfolio returns.

It is also worth noting the similarity in the magnitudes of the liquidity risk effect for both net and gross returns. It is interesting that managers appear to generate a conditional liquidity risk premium for their funds and yet capture little to none of it through expenses. The most likely explanation is that since the abnormal returns to holdings liquidity risk are small on average and expenses are sticky, equilibrium cash flow adjustment (Berk and Green (2004)) dictates managers pass on positive returns to liquidity risk to investors during non-liquidity crisis periods (and, conversely, pass on negative returns to liquidity risk during high illiquidity periods).

6. Joint Analysis of Liquidity and Liquidity Risk Premia

While the results in the previous sections suggest liquidity and liquidity risk impact fund returns, the close relation between the two require both be tested jointly. Illiquid assets are inherently sensitive to changes in market liquidity (Acharya and Pedersen (2005), Watanabe and Watanabe (2008)), implying the high expected returns generated by illiquid assets may be due, in part or in total, to liquidity risk. It is therefore important to test the two effects jointly in order to correctly attribute their impacts on fund returns. I therefore combine the models from Tables 7 and 8 and run pooled OLS regressions of excess and risk-adjusted returns on cross-sectionally standardized holdings liquidity beta, holdings *Amihud* liquidity level, high illiquidity regime indicator, the interaction between the indicator and liquidity beta, the interaction between the indicator

and liquidity, and previously discussed fund characteristic controls. The coefficients from these regressions are presented in Table 9.[38]

Overall, the liquidity and liquidity risk premia appear to be separate effects. Interestingly, while the impact of liquidity on fund returns remains strong for raw and single factor alphas, it is weaker for three- and four-factor alphas. Table 7 reported a one standard deviation increase in *Amihud* predicts an increase in annual gross four-factor alpha of 48 basis points (*t*-statistic of 1.98). In Table 9, that relation is an economically similar 36 basis points, but with a weaker *t*-statistic of 1.47. The estimated conditional liquidity premium is robust to inclusion all three liquidity beta measures. Jointly tested, liquidity strongly impacts raw returns and single-factor alphas, but has a much smaller impact on three- and four-factor alphas.

The liquidity risk premium in fund returns is robust to the inclusion of liquidity. A one standard deviation increase in *Pastor-Stambaugh* beta predicts an increase in raw (risk-adjusted) net returns of 156 (84) basis points annually during non-liquidity crisis months. An increase in *Amihud* beta predicts an increase of 84 (48) basis points. The *Sadka* liquidity beta demonstrates the weakest relation to returns. While unconditional analysis in Table 7 reveals a significant relation between fund holdings *Sadka* beta and raw and single factor risk-adjusted returns, conditional analysis reveals a statistically insignificant relation of only 24 (12) basis points.

My conclusion from the evidence presented in Table 9 is that jointly tested both liquidity and liquidity risk impact fund returns. As the two measures are related, I expect

[38] As liquidity and liquidity risk are correlated, there is some concern of multicolinearity in this multivariate setting. Variance inflation factors for all coefficients in these regressions are all below 1.6, suggesting they are unbiased.

both effects to weaken when included in the same regression. However, *Pastor-Stambaugh* and *Amihud* betas reveal a significant liquidity risk premium while mean holdings *Amihud* reveals a jointly significant liquidity premium. The two effects, while related, independently impact fund returns.

7. Conclusion

In this paper, I examine the impact of liquidity and liquidity risk on equity mutual fund returns. This analysis is important both for understanding the determinants of mutual fund performance and gaining additional insight into the liquidity and liquidity risk premia. Overall, I find that liquidity and liquidity risk impact equity mutual fund returns during my sample period of 1984 through 2008. A one standard deviation increase in fund illiquidity is associated with an increase in annualized fund return of as much as 1.08 percent while an increase in holdings liquidity beta results in an increase in annualized fund returns of as much as 0.96 percent.

As theory suggests both the liquidity and liquidity risk premia are time-varying in relation to market liquidity, I introduce an indicator variable for high market illiquidity periods to both liquidity and liquidity risk analyses. I find that both effects invert during these liquidity crises. Excluding extremely illiquid months for the analysis reveals a stronger liquidity premium and, in contrast to unconditional results, a statistically and economically significant liquidity risk premium in fund returns.

Finally, I test both liquidity and liquidity risk effects simultaneously and find evidence that both impact fund returns. Excluding periods of high aggregate illiquidity, a one standard deviation in *Pastor-Stambaugh* liquidity beta predicts an increase of 1.56

percent annualized return while an increase in *Amihud* liquidity increases returns by 1.32 percent. Overall, I conclude the liquidity characteristics of fund holdings have a substantial impact on returns. The liquidity and liquidity risk premia are time varying and, most importantly, both independently impact mutual fund returns.

Appendix 1

I begin with all fund share classes in the CRSP Mutual Fund Database with Lipper objective codes which suggest an investment focus of growth (ELCC, G, LCCE, LCGE, LCVE, MLCE, MLGE, MLVE, SESE), growth and income (EI, EIEI, GI, I), small capitalization (MC, MCCE, MCGE, MCVE, SCCE, SCGE, SCVE, SG) and aggressive growth (CA, MR). This removes all funds with bond, mixed, derivatives, leverage, emerging markets or international investment objectives.

Fund share classes are aggregated into fund level portfolios by matching their holdings portfolios with MFLINKs. This portfolio matching strategy does not work for funds without reported holdings, but as I require fund holdings to calculate fund liquidity and liquidity betas this problem has no impact on my study. Aggregate fund characteristics are measured as either the total net asset value weighted means of share class characteristics (net return, expense ratio, turnover, loads, asset flow), the sum of share class characteristics (total net assets) or, in the case of age, the oldest share class in the fund. As new funds are often subsidized by their fund families (incubation bias, Evans (2010)) I include funds only once their total aggregate portfolio total net assets exceed 15 million dollars. Also, as a significant portion of funds report only annual earnings prior to 1984 (Elton, Gruber and Blake (2001)) I exclude fund observations prior to 1984.

Funds are then matched to their equity holdings in the Thomson CDA/Spectrum database using MFLINKs. In order for a fund observation to be included in my final sample it must have a return and total net assets reported in CRSP and have holdings

reported in the Thomson CDA/Spectrum database. My final sample consists of 2,480 funds and 210,100 fund month observations.

Figure 1

The line graph represents the innovations in equal weighted market normalized Amihud measure, assuming an AR(2) process, between January 1984 and December 2008. The light gray shaded areas represent months classified as in recession by the National Bureau of Economic Research. The dark gray shaded areas represent months traditionally identified as market liquidity crises (October and November 1987, October and November 1989, October and November 1997, August and September 1998, July and August 2007 and June through December 2008). The horizontal line across the y-axis is the value of the 80th percentile of normalized Amihud innovations, and all months with values above are classified as high liquidity periods.

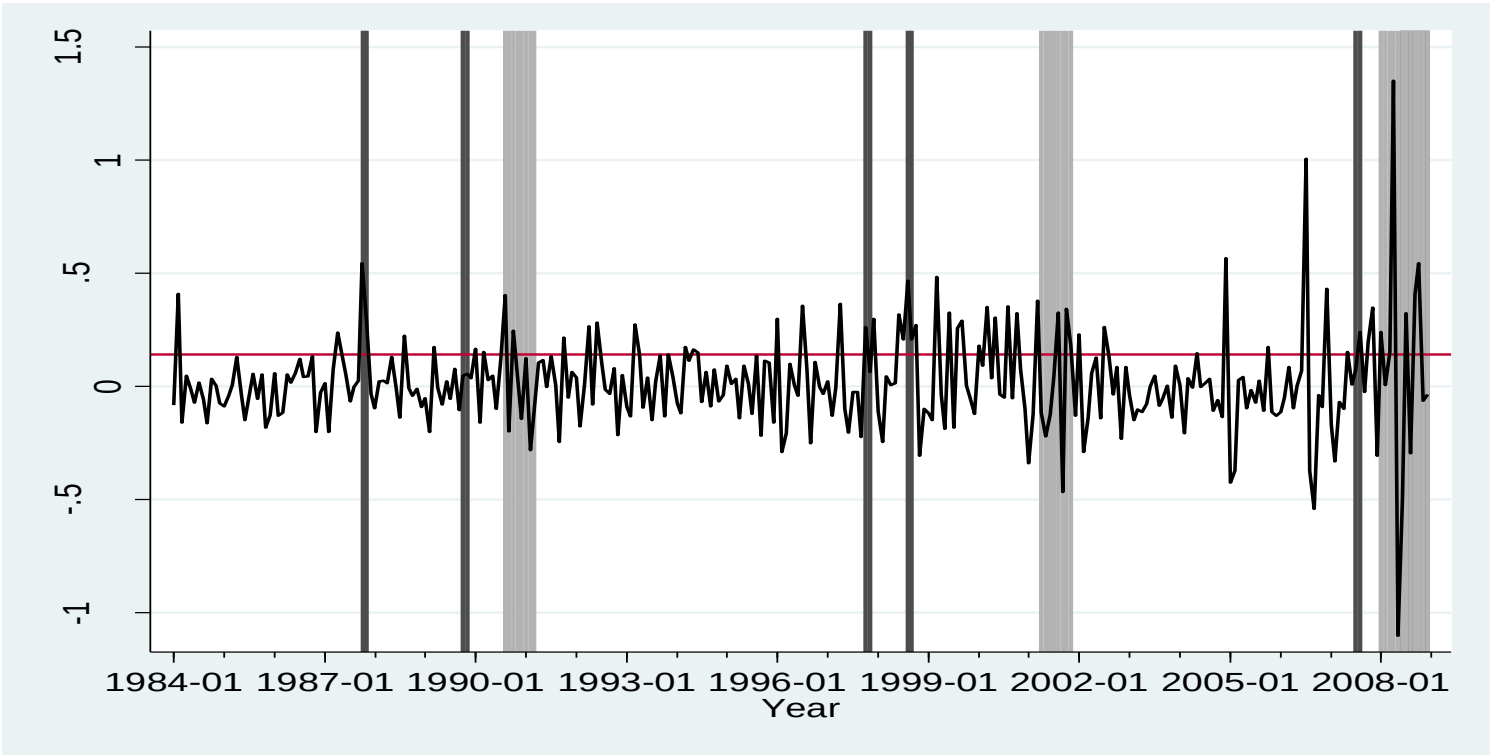

Table 1

The sample is generated from all mutual funds in the CRSP Survivor-bias-free Mutual Fund Database, retaining only funds which are actively managed and have Lipper Objective codes showing they invest only in domestic equities between January 1984 and December 2008. Individual fund share classes are aggregated to form a single observation per fund per month. Equity funds are matched to their holdings in the Thomson CDA/Spectrum database through MFLINKs. Funds are only included in the sample once they have exceeded 15 million dollars in assets. Panel A reports the size of the sample. Panel B reports the times series means of monthly cross sectional means, medians and standard deviations of fund characteristics. Total Net Assets is the aggregate market value (in millions) of all assets held by all share classes of a fund. Total Family Assets is the aggregate market value (in millions) of all assets held by each fund management company. Age is the number of years since the fund's oldest share class was first issued. Net Asset Flow is the percentage change in Total Net Assets not attributable to fund returns over the previous month, and is Winsorized at the 1st and 99th percentiles. Max Load is the maximum of the fund's front and rear load. Cash is the percent of fund TNA held in cash. Expense Ratio is the annual percentage charged on assets under management and Turnover Ratio is annual asset purchases divided by assets under management. Size, Book/Market and Momentum are the mean quintile rankings of fund equity holdings as defined by Daniel, Grinblatt, Titman and Wermers (1997).

Panel A: Sample Size	
Number of Funds	2,480
Number of Observations	210,110

Panel B: Fund Characteristics	Mean	Median	Standard Deviation
Total Net Assets (mil)	$1,018	$234	$3,140
Total Family Assets (mil)	$13,663	$3,042	$29,900
Age	14	12	10
Flow (Monthly)	1.06%	0.03%	5.89%
Max Load	6.68%	7.26%	2.48%
Cash (Percent of Assets)	7.14%	4.91%	8.41%
Expense Ratio	1.18%	1.12%	0.55%
Turnover	83.03%	61.33%	89.95%

Table 2

Common stocks are sorted into portfolios every December by their mean monthly liquidity value over the previous 12 months and portfolios are held for the following year. Amihud is defined as the equal-weighted monthly mean of daily dollar volume price impact, in millions (Amihud (2002)), generated from daily CRSP file for 1984 through 2008. ESpread is defined as the monthly dollar-volume weighted mean of transaction log effective spread (Goyenko, Trzcinki and Holden (2010)), generated from TAQ for 1993 through 2008. Panel A reports the equal weighted mean liquidity measure and raw and risk adjusted portfolio returns for funds sorted by the previous year's mean liquidity. Row 10-1 (9-2) is the time series mean of the difference in returns between the 10 (9) and 1 (2) deciles. Panel B reports the coefficients of both cross sectional and panel regressions of equity raw and risk adjusted returns on the prior year's cross-sectionally standardized (~N(0,1)) mean liquidity. Regressions are univariate. Risk adjusted returns for portfolios are generated using single factor (CAPM), three factor (Fama French) and four factor (Carhart) time series models. Risk adjusted returns used as dependent variables for regressions are generated from a rolling 60 (minimum 48) month regressions of equity excess returns on either the single-, three- or four-factor models. *t*-statistics for panel regressions are generated from standard errors clustered by time and stock.

Panel A: Portfolio Sorting

Liquidity Portfolios	Amihud	Amihud (1984-2008) Ret	α_1	α_3	α_4	ESpread	Effective Spread (1993-2008) Ret	α_1	α_3	α_4
1	0.002	0.94%	0.10%	0.08%	0.11%	0.29%	0.73%	0.09%	0.06%	0.15%
2	0.014	0.87%	-0.02%	-0.04%	-0.03%	0.45%	0.70%	0.01%	-0.07%	-0.01%
3	0.046	0.90%	0.00%	-0.02%	-0.01%	0.62%	0.74%	0.04%	-0.04%	0.00%
4	0.118	0.89%	-0.01%	-0.03%	0.00%	0.81%	0.80%	0.10%	0.01%	-0.01%
5	0.264	0.97%	0.09%	0.07%	0.02%	1.01%	0.85%	0.16%	0.04%	0.05%
6	0.499	1.07%	0.17%	0.14%	0.08%	1.28%	0.77%	0.05%	-0.03%	-0.08%
7	0.925	1.19%	0.31%	0.28%	0.22%	1.64%	0.96%	0.23%	0.15%	0.08%
8	1.634	1.25%	0.42%	0.31%	0.24%	2.08%	1.25%	0.51%	0.43%	0.33%
9	3.049	1.39%	0.56%	0.45%	0.34%	2.79%	1.30%	0.57%	0.49%	0.37%
10	8.638	2.18%	1.28%	1.20%	1.05%	4.39%	2.14%	1.36%	1.31%	1.10%
10-1	8.636	1.24%	1.18%	1.12%	0.94%	4.10%	1.41%	1.27%	1.25%	0.95%
		(4.69)	(4.46)	(4.92)	(4.05)		(3.76)	(3.55)	(3.91)	(2.99)
9-2	3.035	0.52%	0.58%	0.49%	0.37%	2.34%	0.60%	0.56%	0.56%	0.38%
		(5.39)	(5.31)	(5.39)	(4.57)		(4.14)	(3.95)	(4.27)	(3.41)

Panel B: Regressions

	Amihud (1984 - 2008) Ret	α_1	α_3	α_4	Effective Spread (1993-2008) Ret	α_1	α_3	α_4
Fama-MacBeth	0.33	0.34	0.34	0.35	0.36	0.30	0.34	0.36
	(6.11)	(5.74)	(6.30)	(6.49)	(3.34)	(2.55)	(3.60)	(3.65)
Pooled	0.35	0.36	0.35	0.37	0.38	0.31	0.35	0.37
	(6.35)	(6.70)	(7.08)	(7.15)	(3.56)	(2.94)	(3.84)	(3.93)

Table 3

All funds are assigned a liquidity measure defined as the value-weighted mean of the liquidity of their equity holdings. Panel A reports the equal weighted mean fund characteristics of portfolios sorted by prior year's Amihud measure. TNA and FTNA are fund and family total net assets, in millions. Asset flow is the monthly change in net total assets unexplained by fund returns. Cash is the percent of total net assets held in cash. Age is the number of years since the fund's oldest share class was issued. Expense ratio is 1/12 the annual reported expense ratio. Turnover ratio is the annual turnover ratio as reported by CRSP. Max load is the maximum of the highest front and rear end loads. Panel B reports the equal weighted raw and risk adjusted net and gross returns for each Amihud liquidity decile portfolio. Panel C reports the equal weighted raw and risk adjusted net and gross returns for each Effective Spread liquidity decile portfolio. Panel D reports coefficients from cross sectional and pooled OLS regressions of raw and risk adjusted returns on the prior year's cross-sectionally normalized mean liquidity (~N(0,1)) and normalized fund characteristics. Lagged fund TNA, family TNA, Expense Ratio, Turnover, Max Load, Asset Flow and Returns are used as in Chen et al. (2004), though only the coefficients on lagged liquidity are reported. Risk adjusted returns for portfolios are generated using single factor (CAPM), three factor (Fama French) and four factor (Carhart) time series models. Risk adjusted returns used as dependent variables for regressions are generated from a rolling 60 (minimum 48) month regressions of fund excess returns on either the single-, three- or four-factor models. Gross returns are net returns plus estimated monthly transaction costs (Wermers (2000)) plus 1/12 the fund's annual expense ratio. *t*-statistics for pooled OLS regressions are generated from standard errors clustered by time and fund, and are reported in parentheses below.

Panel A: Fund Characteristics (Amihud: 1984-2008)

Liquidity Portfolios	Cash	TNA	Asset Flow	Age	Expense Ratio	Turnover Ratio	Max Load
1	5.81%	$2,304	0.46%	19	1.09%	65.57%	5.63%
2	6.31%	$1,230	0.21%	18	1.08%	70.46%	5.69%
3	6.75%	$1,466	0.31%	19	1.09%	86.57%	5.71%
4	7.21%	$1,387	0.23%	19	1.12%	84.26%	5.37%
5	7.11%	$1,387	0.30%	18	1.13%	82.30%	5.37%
6	7.71%	$1,087	0.18%	17	1.15%	87.96%	5.27%
7	7.60%	$1,004	0.43%	17	1.22%	75.66%	5.10%
8	8.27%	$728	0.57%	15	1.22%	84.71%	5.08%
9	8.64%	$781	0.44%	14	1.25%	75.65%	5.03%
10	8.02%	$681	0.92%	13	1.34%	59.14%	4.72%

Panel B: Portfolio Sorting (Amihud: 1984-2008)

Liquidity		Net				Gross			
Portfolios	Amihud	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
1	0.001	0.90%	-0.12%	-0.09%	-0.06%	1.02%	0.01%	0.04%	0.06%
2	0.002	0.93%	-0.08%	-0.10%	-0.06%	1.07%	0.06%	0.04%	0.08%
3	0.004	0.95%	-0.07%	-0.07%	-0.11%	1.11%	0.09%	0.09%	0.05%
4	0.005	0.99%	-0.05%	-0.06%	-0.08%	1.15%	0.10%	0.09%	0.08%
5	0.008	1.01%	-0.03%	-0.06%	-0.06%	1.19%	0.15%	0.12%	0.13%
6	0.012	1.03%	-0.01%	-0.04%	-0.02%	1.22%	0.18%	0.15%	0.16%
7	0.022	0.99%	-0.09%	-0.08%	-0.07%	1.17%	0.09%	0.10%	0.11%
8	0.039	1.11%	0.02%	0.02%	0.02%	1.30%	0.22%	0.22%	0.21%
9	0.068	1.11%	0.00%	0.00%	-0.04%	1.31%	0.21%	0.20%	0.16%
10	0.263	1.10%	0.05%	-0.03%	0.00%	1.31%	0.26%	0.18%	0.21%
10-1	0.262	0.20%	0.17%	0.06%	0.06%	0.29%	0.25%	0.14%	0.15%
		(1.35)	(1.11)	(0.86)	(0.97)	(1.96)	(1.70)	(2.21)	(2.23)

Panel C: Portfolio Sorting (Effective Spread: 1993-2008)

Liquidity Portfolios	ESpread	Net Ret	Net α_1	Net α_3	Net α_4	Gross Ret	Gross α_1	Gross α_3	Gross α_4
1	0.21%	0.74%	-0.17%	-0.11%	-0.09%	0.86%	-0.06%	0.00%	0.03%
2	0.23%	0.69%	-0.21%	-0.20%	-0.15%	0.81%	-0.09%	-0.09%	-0.03%
3	0.25%	0.73%	-0.14%	-0.20%	-0.16%	0.85%	-0.02%	-0.08%	-0.04%
4	0.27%	0.78%	-0.07%	-0.17%	-0.09%	0.93%	0.07%	-0.03%	0.06%
5	0.30%	0.90%	0.00%	-0.04%	-0.09%	1.05%	0.14%	0.10%	0.05%
6	0.33%	0.89%	-0.03%	-0.09%	-0.14%	1.06%	0.13%	0.08%	0.03%
7	0.39%	0.88%	-0.03%	-0.13%	-0.12%	1.04%	0.13%	0.03%	0.04%
8	0.49%	0.84%	-0.14%	-0.26%	-0.23%	1.02%	0.04%	-0.08%	-0.06%
9	0.61%	0.92%	-0.04%	-0.13%	-0.21%	1.10%	0.14%	0.06%	-0.02%
10	0.83%	1.03%	0.09%	-0.07%	-0.07%	1.23%	0.29%	0.13%	0.13%
10-1	0.62%	0.29%	0.26%	0.04%	0.02%	0.37%	0.35%	0.13%	0.10%
		(1.29)	(1.17)	(0.44)	(0.17)	(1.70)	(1.57)	(1.33)	(1.00)

Panel D: Regressions								
	Net				Gross			
	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
Amihud (1984-2008)								
Fama-MacBeth	0.05	0.03	0.05	0.06	0.07	0.07	0.07	0.09
	(1.42)	(0.92)	(1.99)	(2.76)	(1.60)	(1.71)	(2.70)	(3.25)
Pooled	0.07	0.06	0.00	0.02	0.09	0.07	0.01	0.02
	(2.64)	(2.28)	(0.24)	(1.20)	(3.00)	(2.69)	(0.74)	(1.61)
ESpread (1993-2008)								
Fama-MacBeth	0.09	0.08	0.02	0.02	0.11	0.13	0.05	0.06
	(1.33)	(1.28)	(0.56)	(0.91)	(1.57)	(1.98)	(1.74)	(2.33)
Pooled	0.12	0.10	-0.01	0.00	0.16	0.12	0.02	0.03
	(2.14)	(1.77)	(-0.34)	(0.05)	(2.61)	(2.17)	(0.83)	(1.27)

Table 4

Liquidity betas are estimated using 60 month (minimum 48 months) rolling regressions of excess returns on market liquidity innovations and the four Carhart factors. All common equity (share codes 10 and 11) with a share price in excess of 1 dollar are included in the sample. Market liquidity innovations are defined as the residuals from an AR(2) process of the equal-weighted normalized Amihud measure (Acharya and Pedersen (2005) or PS measure (Pastor and Stambaugh (2003), or as the permanent variable component Sadka measure (Sadka (2006)). Panel A reports the raw and risk adjusted returns of equal-weighted portfolios sorted monthly by lagged liquidity betas. Panel B reports the coefficients of both cross sectional and panel regressions of equity raw and risk adjusted returns on lagged cross-sectionally normalized (~N(0,1)) liquidity betas. Regressions are univariate. Risk adjusted returns for portfolios are generated using single factor (CAPM), three factor (Fama French) and four factor (Carhart) time series models. Risk adjusted returns used as dependent variables for regressions are generated from a rolling 60 (minimum 48) month regressions of fund excess returns on either the single-, three- or four-factor models. *t*-statistics for panel regressions are generated from standard errors clustered by time and stock.

Panel A: Portfolio Sorting

Liquidity Beta	AmihudN				Pastor-Stambaugh				Sadka			
Portfolios	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
1	0.86%	-0.05%	-0.13%	0.12%	1.00%	0.09%	-0.02%	0.27%	1.05%	0.19%	0.08%	0.33%
2	1.02%	0.16%	0.01%	0.22%	1.01%	0.18%	-0.01%	0.19%	0.95%	0.19%	-0.04%	0.19%
3	1.00%	0.20%	0.01%	0.14%	1.04%	0.24%	0.06%	0.19%	0.96%	0.25%	0.05%	0.21%
4	0.99%	0.22%	0.02%	0.12%	0.96%	0.19%	-0.01%	0.11%	0.94%	0.26%	0.07%	0.20%
5	0.97%	0.22%	0.04%	0.14%	1.03%	0.28%	0.10%	0.20%	0.90%	0.23%	0.02%	0.14%
6	1.07%	0.32%	0.15%	0.26%	0.93%	0.18%	0.00%	0.08%	1.03%	0.34%	0.14%	0.30%
7	1.03%	0.26%	0.08%	0.18%	1.06%	0.28%	0.11%	0.25%	0.99%	0.28%	0.08%	0.24%
8	1.14%	0.33%	0.15%	0.33%	1.10%	0.28%	0.12%	0.28%	1.13%	0.40%	0.19%	0.40%
9	1.15%	0.31%	0.14%	0.35%	1.12%	0.25%	0.13%	0.36%	1.22%	0.45%	0.26%	0.53%
10	1.15%	0.23%	0.19%	0.55%	1.14%	0.21%	0.18%	0.48%	1.29%	0.46%	0.31%	0.72%
10-1	0.29%	0.28%	0.32%	0.43%	0.14%	0.12%	0.20%	0.21%	0.24%	0.27%	0.23%	0.39%
	(1.76)	(1.74)	(1.97)	(2.57)	(0.85)	(0.78)	(1.29)	(1.36)	(1.24)	(1.40)	(1.14)	(1.96)

Panel B: Regressions

	AmihudN				Pastor-Stambaugh				Sadka			
	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
Fama-MacBeth	0.09	0.11	0.10	0.15	0.06	0.11	0.11	0.14	0.07	0.09	0.10	0.14
	(2.08)	(2.63)	(2.14)	(2.77)	(1.12)	(2.22)	(2.10)	(2.44)	(1.19)	(1.58)	(1.38)	(1.78)
Pooled	0.09	0.11	0.10	0.15	0.05	0.10	0.11	0.14	0.08	0.10	0.10	0.14
	(1.98)	(2.47)	(2.03)	(2.78)	(1.22)	(2.31)	(2.26)	(2.93)	(1.41)	(1.70)	(1.58)	(2.15)

Table 5

Equity liquidity betas (EBeta) are estimated using 60 month (minimum 48 months) rolling regressions of excess returns on market liquidity innovations and the four Carhart factors. All common equity (share codes 10 and 11) with share price in excess of 1 dollar are included in the sample. Fund liquidity betas are measured as either the value-weighted mean of holdings equity liquidity betas (HBeta) or from rolling regressions of fund returns on market liquidity innovations (FBeta), in a procedure identical to equity betas. Market liquidity innovations are defined as the residuals from an AR(2) process of the equal-weighted normalized Amihud measure (Acharya and Pedersen (2005) or PS measure (Pastor and Stambaugh (2003), or as the permanent variable component Sadka measure (Sadka (2006)). Reported are the time series means of cross sectional summary statistics holdings-based betas (HBeta), fund-return based betas (FBeta) and pairwise difference between the two (|H-F|). Means are computed as the time series means of cross sectional means.

	AmihudN			PS			Sadka		
	HBeta	FBeta	|H-F|	HBeta	FBeta	|H-F|	HBeta	FBeta	|H-F|
Mean	-0.007	-0.003	0.015	-0.016	-0.006	0.047	-0.250	-0.025	0.542
P1	-0.069	-0.054	0.000	-0.173	-0.162	0.001	-2.055	-1.485	0.008
P5	-0.043	-0.035	0.001	-0.112	-0.094	0.003	-1.318	-0.904	0.037
P10	-0.032	-0.025	0.002	-0.087	-0.071	0.006	-1.017	-0.673	0.073
P25	-0.018	-0.013	0.005	-0.050	-0.038	0.016	-0.601	-0.339	0.187
P50	-0.005	-0.002	0.011	-0.015	-0.004	0.035	-0.232	-0.022	0.403
P75	0.005	0.008	0.020	0.018	0.027	0.064	0.101	0.292	0.738
P90	0.016	0.016	0.033	0.053	0.058	0.101	0.476	0.628	1.173
P95	0.025	0.023	0.043	0.078	0.080	0.131	0.773	0.847	1.505
P99	0.046	0.039	0.072	0.145	0.122	0.211	1.585	1.386	2.398

Table 6

Fund and holdings liquidity betas are estimated as described in Table 4. Panel A reports the equal weighted raw and risk adjusted fund returns for portfolios sorted monthly by lagged AmihudN, PS and Sadka fund liquidity betas. . Panel B reports the coefficients of both cross sectional and panel regressions of fund raw and risk adjusted net returns on lagged cross-sectionally normalized (~N(0,1)) fund liquidity betas and fund characteristics. Panel C reports the equal weighted raw and risk adjusted fund returns for portfolios sorted monthly by lagged AmihudN, PS and Sadka holdings liquidity betas. Panel D reports the coefficients of both cross sectional and panel regressions of fund raw and risk adjusted net returns on lagged cross-sectionally normalized (~N(0,1)) holdings liquidity betas and fund characteristics. Lagged fund TNA, family TNA, Expense Ratio, Turnover, Max Load, Asset Flow and Returns are used as in Chen et al. (2004), though only the coefficients on lagged liquidity are reported. Risk adjusted returns for portfolios are generated using single factor (CAPM), three factor (Fama French) and four factor (Carhart) time series models. Risk adjusted returns used as dependent variables for regressions are generated from a rolling 60 (minimum 48) month regressions of fund excess returns on either the single-, three- or four-factor models. *t*-statistics for panel regressions are generated from standard errors clustered by time and stock.

Panel A: Portfolio Sorting (Fund Liquidity Betas)

Liquidity Beta	AmihudN				Pastor-Stambaugh				Sadka			
Portfolios	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
1	0.88%	-0.07%	0.04%	-0.01%	0.88%	-0.03%	0.08%	0.04%	0.76%	-0.06%	-0.08%	-0.11%
2	0.82%	-0.09%	-0.04%	-0.08%	0.76%	-0.12%	-0.07%	-0.09%	0.75%	-0.04%	-0.08%	-0.10%
3	0.86%	-0.01%	0.00%	-0.02%	0.77%	-0.10%	-0.07%	-0.09%	0.75%	-0.03%	-0.07%	-0.07%
4	0.78%	-0.08%	-0.10%	-0.11%	0.76%	-0.11%	-0.10%	-0.11%	0.73%	-0.04%	-0.09%	-0.09%
5	0.79%	-0.06%	-0.09%	-0.09%	0.80%	-0.05%	-0.08%	-0.07%	0.73%	-0.05%	-0.09%	-0.10%
6	0.80%	-0.05%	-0.07%	-0.07%	0.79%	-0.06%	-0.09%	-0.10%	0.76%	-0.01%	-0.06%	-0.06%
7	0.78%	-0.06%	-0.10%	-0.09%	0.81%	-0.03%	-0.08%	-0.06%	0.78%	-0.01%	-0.05%	-0.05%
8	0.79%	-0.05%	-0.10%	-0.09%	0.88%	0.04%	-0.04%	-0.04%	0.73%	-0.06%	-0.09%	-0.08%
9	0.84%	0.01%	-0.04%	-0.03%	0.89%	0.04%	-0.04%	-0.03%	0.82%	0.02%	-0.01%	-0.03%
10	0.84%	0.02%	-0.05%	-0.03%	0.85%	-0.02%	-0.08%	-0.06%	0.82%	0.01%	-0.03%	-0.03%
10-1	-0.04%	0.09%	-0.09%	-0.02%	-0.03%	0.01%	-0.16%	-0.10%	0.06%	0.07%	0.05%	0.08%
	(-0.30)	(0.84)	(-1.13)	(-0.23)	(-0.32)	(0.09)	(-1.71)	(-1.06)	(0.69)	(0.73)	(0.55)	(0.81)

Panel B: Regressions (Fund Liquidity Betas)

	AmihudN				Pastor-Stambaugh				Sadka			
	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
Fama-MacBeth	-0.00	0.03	0.01	0.01	0.01	0.00	-0.03	-0.02	0.03	0.03	0.01	0.02
	(-0.13)	(1.57)	(0.38)	(0.39)	(0.30)	(0.02)	(-1.69)	(-1.34)	(1.23)	(1.07)	(0.86)	(1.01)
Pooled	0.01	0.04	0.01	0.02	0.01	0.06	-0.01	-0.00	0.01	0.04	0.04	0.04
	(0.26)	(1.25)	(0.71)	(0.78)	(0.25)	(1.56)	(-0.49)	(-0.00)	(0.27)	(1.48)	(2.01)	(2.19)

Panel C: Portfolio Sorting (Holdings Liquidity Betas)

Liquidity Beta	AmihudN				Pastor-Stambaugh				Sadka			
Portfolios	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
1	0.81%	-0.15%	0.02%	-0.06%	0.82%	-0.09%	0.01%	-0.01%	0.69%	-0.16%	-0.11%	-0.16%
2	0.84%	-0.06%	0.02%	-0.04%	0.80%	-0.08%	-0.04%	-0.03%	0.72%	-0.09%	-0.09%	-0.10%
3	0.86%	-0.01%	0.03%	-0.01%	0.80%	-0.08%	-0.04%	-0.05%	0.79%	0.00%	-0.04%	-0.03%
4	0.83%	-0.03%	-0.04%	-0.08%	0.78%	-0.07%	-0.07%	-0.07%	0.77%	-0.01%	-0.05%	-0.04%
5	0.87%	0.02%	-0.01%	-0.01%	0.81%	-0.04%	-0.06%	-0.07%	0.78%	0.00%	-0.05%	-0.05%
6	0.83%	-0.01%	-0.05%	-0.05%	0.86%	0.00%	-0.03%	-0.03%	0.76%	-0.01%	-0.07%	-0.05%
7	0.81%	-0.03%	-0.08%	-0.05%	0.83%	-0.02%	-0.07%	-0.07%	0.79%	0.02%	-0.02%	-0.03%
8	0.84%	0.00%	-0.06%	-0.03%	0.89%	0.05%	-0.02%	-0.02%	0.83%	0.04%	0.00%	-0.01%
9	0.87%	0.04%	-0.03%	0.00%	0.91%	0.06%	-0.01%	-0.03%	0.84%	0.05%	0.01%	-0.04%
10	0.89%	0.06%	-0.02%	-0.01%	0.96%	0.09%	0.10%	0.04%	0.98%	0.16%	0.12%	0.06%
10-1	0.08%	0.21%	-0.04%	0.05%	0.14%	0.18%	0.09%	0.05%	0.29%	0.32%	0.23%	0.22%
	(0.56)	(1.67)	(-0.40)	(0.49)	(1.17)	(1.48)	(0.80)	(0.47)	(2.29)	(2.61)	(1.89)	(1.74)

Panel D: Regressions (Holdings Liquidity Betas)

	AmihudN				Pastor-Stambaugh				Sadka			
	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
Fama-MacBeth	0.04	0.02	0.00	0.02	0.01	0.03	0.01	0.01	0.03	0.03	0.01	0.01
	(0.17)	(0.92)	(0.06)	(0.76)	(0.52)	(0.87)	(0.44)	(0.29)	(1.01)	(1.02)	(0.56)	(0.57)
Pooled	0.05	0.05	0.00	0.02	0.03	0.08	0.03	0.03	0.06	0.07	0.03	0.02
	(0.97)	(1.18)	(0.00)	(0.66)	(0.53)	(1.75)	(0.97)	(0.95)	(1.91)	(2.01)	(0.84)	(0.76)

Table 7

All funds are assigned an liquidity measure defined as the value-weighted mean of the liquidity of their equity holdings. Equity Amihud and effective spread measures are calculated as described in Table 2. Crisis is an indicator variable with a value of 1 for the top quintile illiquid months as measured by the innovations in equal-weighted market normalized Amihud liquidity (Acharya and Pedersen (2005)) and 0 otherwise. Coefficients reported are from panel regressions of raw and risk adjusted returns on the prior year's cross sectionally normalized mean liquidity (~N(0,1)), liquidity regime indicator, regime and normalized liquidity indicator interaction, and normalized fund characteristics. Lagged fund TNA, family TNA, Expense Ratio, Turnover, Max Load, Asset Flow and Returns are used as in Chen et al. (2004), though only the coefficients on lagged liquidity, regime and regime and liquidity interaction are reported. Net returns are as reported by CRSP. Gross returns are net returns plus estimated monthly transaction costs (Wermers (2000)) plus 1/12 the fund's annual expense ratio. Risk adjusted returns used as dependent variables for regressions are generated from a rolling 60 (minimum 48) month regressions of fund excess returns on either the single-, three-, or four-factor (Carhart) models. *t*-statistics for panel regressions are generated from standard errors clustered by time and fund, and are reported in italics below.

	Net				Gross			
	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
Amihud	0.10	0.12	0.02	0.04	0.11	0.11	0.02	0.04
	(2.93)	(3.91)	(1.20)	(2.23)	(3.04)	(3.85)	(1.08)	(1.98)
Crisis*Amihud	-0.11	-0.24	-0.07	-0.08	-0.10	-0.20	-0.04	-0.05
	(-1.33)	(-3.45)	(-2.75)	(-2.97)	(-1.28)	(-3.09)	(-1.37)	(-1.68)
Crisis	-2.53	-0.21	0.13	0.16	-2.05	-0.22	0.11	0.15
	(-2.46)	(-1.76)	(1.23)	(1.46)	(-2.35)	(-1.73)	(0.96)	(1.31)
ESpread	0.24	0.22	0.02	0.02	0.25	0.22	0.04	0.04
	(3.40)	(3.31)	(0.57)	(0.93)	(3.40)	(3.32)	(1.24)	(1.65)
Crisis*ESpread	-0.46	-0.46	-0.09	-0.09	-0.39	-0.41	-0.06	-0.06
	(-3.18)	(-3.58)	(-1.74)	(-1.60)	(-2.80)	(-3.10)	(-1.10)	(-1.01)
Crisis	-2.37	-0.23	0.14	0.16	-1.83	-0.23	0.13	0.15
	(-2.17)	(-1.79)	(1.23)	(1.38)	(-1.96)	(-1.74)	(1.00)	(1.27)

Table 8

Fund and holdings liquidity betas are estimated as described in Table 4. Crisis is an indicator variable with a value of 1 for the top quintile illiquid months as measured by the innovations in equal-weighted market normalized Amihud liquidity (Acharya and Pedersen (2005)) and 0 otherwise. Coefficients reported are from regressions of raw and risk adjusted fund excess net and gross returns on cross-sectionally normalized liquidity betas (~N(0,1)), liquidity regime indicator variable, the interaction of liquidity beta and regime indicator, and fund controls (Chen et al. (2004)) which include fund holdings Amihud liquidity. For brevity, only the coefficients for liquidity betas, regime and interactions with liquidity regime and beta are reported. Net returns are as reported by CRSP. Gross returns are net returns plus estimated monthly transaction costs (Wermers (2000)) plus 1/12 the fund's annual expense ratio. Risk adjusted returns used as dependent variables for regressions are generated from a rolling 60 (minimum 48) month regressions of fund excess returns on either the single-, three- or four-factor (Carhart) models. *t*-statistics, based on standard errors clustered by fund and time are reported below.

	Net				Gross			
	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
Amihud								
Beta	0.07	0.09	0.05	0.07	0.08	0.09	0.06	0.08
	(1.29)	(1.91)	(1.22)	(2.19)	(1.36)	(1.80)	(1.46)	(2.20)
Crisis *Beta	-0.07	-0.14	-0.19	-0.21	-0.07	-0.13	-0.21	-0.22
	(-0.51)	(-1.24)	(-2.32)	(-2.71)	(-0.49)	(-1.02)	(-2.23)	(-2.44)
Crisis	-2.47	-0.22	0.15	0.19	-2.01	-0.19	0.15	0.19
	(-2.46)	(-1.73)	(1.35)	(1.74)	(-2.33)	(-1.47)	(1.26)	(1.64)
Pastor-Stambaugh								
Beta	0.13	0.16	0.08	0.07	0.14	0.17	0.07	0.07
	(2.95)	(3.20)	(2.17)	(2.40)	(3.07)	(3.36)	(2.01)	(2.07)
Crisis *Beta	-0.41	-0.33	-0.19	-0.19	-0.39	-0.33	-0.18	-0.18
	(-2.89)	(-3.21)	(-2.47)	(-2.49)	(-2.76)	(-3.08)	(-2.06)	(-2.18)
Crisis	-2.47	-0.22	0.15	0.19	-2.01	-0.19	0.15	0.19
	(-2.47)	(-1.74)	(1.35)	(1.74)	(-2.33)	(-1.48)	(1.25)	(1.64)
Sadka								
Beta	0.06	0.05	0.02	0.02	0.08	0.07	0.04	0.04
	(1.42)	(1.39)	(0.53)	(0.73)	(1.77)	(1.60)	(1.08)	(1.18)
Crisis *Beta	0.05	0.06	0.03	-0.00	0.06	0.06	0.01	-0.03
	(0.51)	(0.83)	(0.40)	(-0.04)	(0.69)	(0.65)	(0.08)	(-0.36)
Crisis	-2.36	-0.23	0.15	0.19	-1.86	-0.20	0.16	0.19
	(-2.32)	(-1.78)	(1.37)	(1.73)	(-2.13)	(-1.52)	(1.29)	(1.64)

Table 9

Fund and holdings liquidity betas are estimated as described in Table 4. Amihud is defined in described in Table 2. Crisis is an indicator variable with a value of 1 for the top quintile illiquid months as measured by the innovations in equal-weighted market normalized Amihud liquidity (Acharya and Pedersen (2005)) and 0 otherwise. Coefficients reported are from regressions of raw and risk adjusted fund excess net and gross returns on cross-sectionally normalized liquidity betas (~N(0,1)), liquidity regime indicator variable, the interaction of liquidity beta and regime indicator, and fund controls (Chen et al. (2004)) which include fund holdings Amihud liquidity. For brevity, only the coefficients for liquidity betas, regime, interactions with liquidity regime and beta, liquidity and interactions with liquidity are reported. Net returns are as reported by CRSP. Gross returns are net returns plus estimated monthly transaction costs (Wermers (2000)) plus 1/12 the fund's annual expense ratio. Risk adjusted returns used as dependent variables for regressions are generated from a rolling 60 (minimum 48) month regressions of fund excess returns on either the single-, three-, or four-factor models. *t*-statistics, based on standard errors clustered by fund and time are reported below.

	Net				Gross			
	Ret	α_1	α_3	α_4	Ret	α_1	α_3	α_4
Amihud								
Beta	0.07	0.08	0.02	0.04	0.08	0.08	0.03	0.04
	(1.22)	(1.74)	(0.69)	(1.47)	(1.28)	(1.62)	(0.81)	(1.46)
Crisis *Beta	-0.06	-0.09	-0.13	-0.14	-0.06	-0.06	-0.39	-0.15
	(-0.41)	(-0.77)	(-1.73)	(-1.93)	(-0.42)	(-0.48)	(-1.65)	(-1.83)
Amihud	0.11	0.12	0.01	0.03	0.12	0.11	0.01	0.03
	(3.02)	(3.72)	(0.70)	(1.62)	(3.12)	(3.51)	(0.61)	(1.41)
Crisis *Amihud	-0.14	-0.27	-0.06	-0.07	-0.11	-0.23	-0.03	-0.04
	(-1.49)	(-3.51)	(-1.82)	(-2.04)	(-1.26)	(-2.87)	(-0.81)	(-1.02)
Crisis	-2.53	-0.22	0.13	0.15	-2.05	-0.22	0.12	0.15
	(-2.46)	(-1.78)	(1.23)	(1.45)	(-2.35)	(-1.74)	(0.97)	(1.32)
Pastor-Stambaugh								
Beta	0.13	0.14	0.07	0.07	0.13	0.16	0.07	0.08
	(2.88)	(2.97)	(2.02)	(2.80)	(2.90)	(3.12)	(2.11)	(2.95)
Crisis *Beta	-0.43	-0.32	-0.16	-0.15	-0.38	-0.31	-0.16	-0.15
	(-2.86)	(-3.04)	(-1.92)	(-1.90)	(-2.63)	(-2.83)	(-1.75)	(-1.84)
Amihud	0.11	0.12	0.01	0.03	0.12	0.11	0.01	0.03
	(2.97)	(3.75)	(0.67)	(1.69)	(3.08)	(3.51)	(0.61)	(1.47)
Crisis *Amihud	-0.14	-0.27	-0.07	-0.09	-0.11	-0.23	-0.04	-0.05
	(-1.59)	(-3.69)	(-2.18)	(-2.43)	(-1.26)	(-2.92)	(-1.05)	(-1.31)
Crisis	-2.53	-0.22	0.13	0.15	-2.05	-0.22	0.11	0.15
	(-2.47)	(-1.79)	(1.22)	(1.44)	(-2.35)	(-1.75)	(0.96)	(1.31)
Sadka								
Beta	0.02	0.03	0.01	0.01	0.03	0.04	0.01	0.01
	(0.59)	(0.87)	(0.17)	(0.54)	(0.81)	(0.91)	(0.29)	(0.63)
Crisis *Beta	0.08	0.14	0.07	0.03	0.09	0.15	0.08	0.04
	(0.79)	(2.12)	(0.96)	(0.60)	(0.96)	(2.07)	(1.09)	(0.77)
Amihud	0.12	0.13	0.02	0.03	0.13	0.12	0.02	0.03
	(3.14)	(3.77)	(0.80)	(1.77)	(3.28)	(3.60)	(0.71)	(1.56)
Crisis *Amihud	-0.17	-0.29	-0.08	-0.09	-0.15	-0.25	-0.06	-0.06
	(-1.82)	(-3.93)	(-2.49)	(-2.64)	(-1.76)	(-3.28)	(-1.35)	(-1.50)
Crisis	-2.41	-0.23	0.14	0.15	-1.90	-0.23	0.12	0.15
	(-2.32)	(-1.83)	(1.23)	(1.42)	(-2.15)	(-1.78)	(0.98)	(1.30)

CHAPTER 2

The Relation between Price and Performance in the Mutual Fund Industry: Is there a Puzzle?

1. Introduction

Mutual fund researchers have long been puzzled by evidence suggesting that investors pay too much for active management. Actively managed funds, on average, underperform their benchmarks after fees (see e.g., Jensen (1968), Fama and French (2010)). Gruber (1996) considers this result puzzling, as apparently investors pay for active management when they could earn higher returns with low-fee passively managed funds. However, this aggregate underperformance does not mean there is no value in active management. Many studies have found evidence of skill in subsets of active fund managers.[39] If skill exists it is rational for investors to pay higher fees to funds with higher performance (Berk and Green (2004)). Yet, recent work by Gil-Bazo and Ruiz-Verdu (2009) shows that funds with higher fees actually have lower before-fee returns than funds with lower fees. If true, this finding deepens the puzzle identified by Gruber (1996), implying not only that investors pay too much when they choose active over passive management but that they irrationally pay more for the active funds that underperform the most.

The purpose of this paper is to examine the relation between fees charged for active management and fund performance. Given the existence of skill in active fund management, the model proposed by Berk and Green (2004) predicts a positive relation

[39] See e.g. Grinblatt and Titman (1992), Brown and Goetzmann (1995), Chevalier and Ellison (1999), Baks (2003), Cohen, Coval and Pastor (2005), Kacperczyk and Seru (2007), Cohen, Frazzini and Malloy (2008), Kacperczyk, Sialm and Zheng (2008), Cremers and Petajisto (2009).

between fees and before-fee (gross) returns. In their model they assume diminishing returns to assets under management and a competitive provision of capital to fund managers. The result is an equilibrium where abnormal fund returns are competed away by investors, leaving all funds with zero expected after-fee (net) returns. As gross returns are net returns plus expenses and net returns are zero, gross returns can only deviate from zero by the fee charged by the fund. This creates a predicted positive one-to-one relation between fees and gross returns.

I begin by replicating the analysis of Gil-Bazo and Ruiz-Verdu (2009) and, when employing the same specification, find the same puzzling negative relation. Regressing four-factor risk-adjusted gross returns on the prior year's expense ratio produces a statistically significant negative coefficient of -0.32.[40] However, this finding is not robust to two alternate specifications. First, regressing raw gross returns on expense ratios produces a positive, though statistically insignificant, coefficient of 0.31. Second, I sort portfolios into decile portfolios annually by expense ratios and find that the top decile outperforms the bottom decile by 14 (6) raw (risk-adjusted) basis points per month. Both alternate specifications suggest a weakly positive relation between expense ratios and gross returns. While neither of these two findings is strong evidence of the positive relation predicted by theory, they do contradict the inverse relation identified by Gil-Bazo and Ruiz-Verdu (2009).

The analysis up to this point is univariate. However, when I control for other fund characteristics I find a significantly positive relation between expense ratios and gross

[40] I note that my sample period of 1984 through 2008 differs from that used by Gil-Bazo and Ruiz-Verdu (2009), 1963 through 2007. Using cross-sectional regressions, they find a univariate coefficient of -1.41. If I use the same sample period I find results which are more similar to theirs (-0.99).

returns. Fees are just one of many mutual fund characteristics identified in the literature which may be related to fund returns (see e.g., Chen et al. (2004)), and expense ratios are highly correlated with many fund characteristics. I therefore utilize a multivariate cross-sectional regression framework, controlling for fund total net assets, family total net assets, holdings liquidity, turnover, loads, annual net asset flow, and the prior year's cumulative returns. Regressing gross four-factor alphas on expense ratios while including these controls reveals a statistically significant coefficient of 0.88. This result is in sharp contrast to the -1.41 univariate coefficient found by Gil-Bazo and Ruiz-Verdui (2009). This positive relation exists for all three models of risk adjustment (single-, three-, and four-factor alphas). These results both contradict the puzzle proposed by Gil-Bazo and Ruiz-Verdu (2009) and support the Berk and Green (2004) model. Overall I conclude that, holding other fund characteristics constant, the incremental relation between expense ratios and gross returns is positive. Investors appear to rationally pay higher prices for funds with higher gross performance.

The total expense ratio is not used in its entirety to compensate managers for performance. 12b-1 fees, which can be as much as 1 percent of fund assets, are collected solely to pay for marketing expenses.[41] Additionally, some of the fees collected are used to pay for administrative, accounting, and legal expenses which should have little impact on gross fund returns.[42] There is, however, a portion of the total expense ratio which is

[41] These marketing and shareholder expenses are allowed under SEC Rule 12b-1, and limited to 0.75 percent of average annual net assets for marketing and 0.25 percent for shareholder services by FINRA Rule 2830. Therefore, funds may charge, in total, as much as 1 percent of average annual net assets as 12b-1 fees.

[42] Fees not classified as management fees or 12b-1 fees (by the SEC definition) are often reported as "Other Expenses" on a fund's prospectus.

used to compensate managers. This management fee is the direct price for active management.

I therefore also examine the relation between management fees and gross returns. Cross-sectional regressions show a strong positive relation between management fees and gross returns both with and without controls. Regressing four-factor risk-adjusted returns on management fees produces a positive coefficient of 0.57 (1.51) without (with) controls. Behaving rationally, investors are willing to pay higher fees for managers who have better gross performance.

The model proposed by Berk and Green (2004) also predicts a more fundamental positive relationship between fees and the skill possessed by managers. I therefore examine how management fees are related to two proxies of manager skill: trading skill (Chen, Jegadeesh and Wermers (2000)) and active share of fund holdings (Cremers and Petajisto (2009)). I define trading skill as the returns on stocks bought by a fund in the prior quarter minus the returns on stocks sold in the prior quarter. To the extent that the active choice to trade a stock better represents manager opinions and ability than the passive choice to continue holding a stock, trading skill is a more accurate measure of manager skill than net or gross returns (Chen et al. (2000)). Active share of holdings is the percentage of holdings which deviate from the closest fund benchmark index. Cremers and Petajisto (2009) finds that funds which systematically deviate from their benchmark index holdings demonstrate skill in active management (and earn higher subsequent returns).

Sorting funds into decile portfolios at the end of every year by either total expense ratio or management fee reveals significant stock selection ability in high fee funds.

Looking at expense ratio portfolios, I find the stocks bought by high expense ratio funds outperform the stocks sold by 18 basis points per month while the stocks bought by low expense ratio funds underperform the stocks sold by 3 basis points per month. This statistically significant 21 basis point per month difference in buy minus sell returns reveals that high expense funds possess considerably more trading skill than low expense funds. Turning to management fees, the relation is slightly weaker but still positive. While the difference in trading skill between the top and bottom management fee deciles is not statistically significant, it is significant for the ninth minus the first decile. High management fee funds have returns to trading skill up to 47 basis points per month higher than funds with the lowest fees. Overall, I interpret these findings as evidence that funds with higher fees possess more skill, consistent with the prediction of the Berk and Green (2004) model.

Examining the active share of holdings, I find a strong positive relation between active share and both expense ratio and management fee. Sorted into deciles by past expense ratios and management fees, the highest expense ratio (management fee) decile has an active share 25.62 (42.26) percent higher than the lowest decile. To the extent that active share is a proxy of manager skill, this is strong evidence that high fee fund managers have considerable more skill than low fee fund managers.

This paper provides several distinct findings which contribute to the mutual fund literature. First, contrary to Gil-Bazo and Ruiz-Verdu (2009), I find strong evidence of a positive relation between expense ratios and gross fund returns. While univariate regressions produce a negative coefficient of -0.32, controlling for other fund characteristics produces a significant positive coefficient of 0.88. Second, I test the

relation between management fees and returns. To my knowledge, I am the first to do so. I find a positive relation between management fees and gross returns both with and without controls for other fund characteristics. Finally, I examine the relation between fees and two proxies of skill (trading skill and active share of holdings). Both are positively related to total expense ratios and management fees. Overall, I find strong support for the prediction of the Berk and Green (2004). The price paid for active management is positively related to performance.

The remainder of this paper is organized as follows. I discuss the theoretical and relation between fees and performance in Section 2. Section 3 details the data used while Section 4 provides the empirical findings. Section 5 concludes.

2. Theoretical Relation between Fees and Performance

The theoretical basis of this paper, as in Gil-Bazo and Ruiz-Verdu (2009), is the model proposed by Berk and Green (2004). Their model begins with the assumption that managers face diminishing marginal returns to assets under management. As fund assets under management increase managers have increased difficulty gathering and trading on sufficient information to generate positive abnormal profits.[43] Managers who reveal skill by performing well see assets under management increase both from returns and from cash inflows. These increased assets then depress future fund returns. The opposite effect occurs when managers reveal poor skill. Investors pull cash out of the fund, decreasing assets under management and increasing the manager's ability to capitalize on private information.

[43] Diminishing returns to assets under management come from two sources. First, as assets increase managers have increased difficulty collecting sufficient information to generate abnormal returns. Second, as assets increase, managers must use larger transactions to capitalize on private information. These larger transactions incur larger transaction costs (predominately through price impact) which decrease abnormal returns.

The result of these cash inflows and outflows is no persistence in net returns. Even given a wide distribution in skill, the competitive provision of capital by investors to funds ensures that, in equilibrium, the expected net-of-fee risk-adjusted return for all mutual funds is zero. This equilibrium condition, $\alpha_i - c_i - f_i = 0$, where α_i is a fund's return to skill, c_i is the trading costs incurred by the fund, and f_i is the fee charged by the fund (as a percentage of fund assets), predicts that gross returns $(\alpha_i - c_i)$ will equal fees (f_i), implying a positive one-to-one relation between fees and gross returns.

This same logic predicts a positive relationship between fees and manager skill.[44] To show this prediction I start with the more general equilibrium condition of the Berk and Green (2004) model:

$$f_i = \alpha_i - \frac{C_i(q_i(\alpha_i))}{q_i(\alpha_i)} \tag{1}$$

where f_i is fund i's fee as a percentage of assets under management, α_i is the fund i's manager's skill, q_i fund i's manager's revenue maximizing level of assets under management and C_i is the trading costs associated with q_i assets under management.

[44] Berk and Green (2004) develop two versions of their model, each with equivalent implications to cash flows. The first assumes managers have complete control over setting their fees and the other assumes fees are set exogenously and managers maximize their income by reducing costs (indexing a portion of their portfolio). I choose the first model (endogenous fees) as the second model (exogenous fees) mechanically removes any relation between fees and skill. Berk and Green (2004) focus on the second model, arguing it is more realistic (i.e. boards set fees). I believe there some evidence to suggest that while managers may not have complete control over setting fees they do have significant influence. Tufano and Sevick (1997) and Ferris and Yan (2007) show funds with fewer independent directors have higher fees (implying manager have greater influence). Mesckhke (2005) finds funds with boards which are less independent, have lower board member ownership and higher unexplained board compensation have higher fees. Moreover, funds with 'good' boards appear to lose skilled managers to funds with higher fees implying managers attempt to match skill to fees even if it requires changing funds managed. In the extreme case Deuskar, Pollet, Wang and Zheng (2009) show that skilled mutual fund managers with capped fees begin managing hedge funds concurrently, implying that managers will maximize their fee income in any way they can (given their skill).

To solve for α_i Berk and Green (2004) assume a functional form for $C_i\big(q_i(\alpha_i)\big)$. In equilibrium they contend managers will set the expected excess return on the marginal dollar invested equal to the marginal cost of expansion implying

$$\alpha_i = c_i'(q_i(\alpha_i)) \tag{2}$$

To ensure decreasing returns to scale on assets under management they also assume $c_i'(q_i(\alpha_i)) > 0$ and $c_i''(q_i(\alpha_i)) > 0$. I therefore apply the following quadratic cost function which meets these two requirements:[45]

$$c_i\big(q_i(\alpha_i)\big) = bq_i(\alpha_i)^2 \tag{3}$$

where b is a positive constant. Assuming that fund managers cannot borrow to increase assets under management, equations (2) and (3) imply

$$q_i(\alpha_i) = \frac{\alpha_i}{2b} \tag{4}$$

Substituting equations (3) and (4) into (1) gives us the relationship between expenses (f_i) and skill (α_i):

$$f_i = \frac{1}{2}\alpha_i \tag{5}$$

which reveals the partial differential of expenses (f_i) with respect to skill (α_i) is

$$\frac{\partial f_i}{\partial \alpha_i} = \frac{1}{2} \tag{6}$$

Therefore, the Berk and Green (2004) model also predicts a positive relationship between fees and manager skill. For a proof of this derivation with a more general k exponential cost function instead of a quadratic function please see Appendix 1.

[45] This is the same cost function adopted by Berk and Green (2004) when they parameterize their model. For further discussion and analysis of the implications of this specification choice see their paper.

3. Data and Summary Statistics

I construct my sample by starting with all equity mutual funds listed in the CRSP Survivorship-Bias Free Mutual Fund Database between 1984 and 2010.[46] Fund share classes are aggregated to form fund portfolios using either the MFLINKs file provided by the Wharton Research Database Service or their fund name as reported in CRSP.[47] To avoid incubation bias I include funds only after their total net assets exceed 15 million dollars (Evans (2010)).[48] Gross returns are defined as net monthly returns plus one twelfth the annual expense ratio. As this study is concerned with active management I eliminate all index funds. Also, to ensure the results are not driven by fee differences between retail and institutional funds I remove all institutional share classes. Fund portfolios are matched to holdings in the Thomson CDA/Spectrum Database using MFLINKs. For a more thorough discussion of the sample construction, please see Appendix 2.

For regressions using fund returns as the dependent variable, a rolling regression approach is used to estimate abnormal returns using a two stage method as outlined by Carhart (1997). As expenses are highly correlated with age and size, I want to use as short a window possible to limit the number of young, small funds removed from the analysis. Every month factor loadings are generated using the prior 12 months of fund

[46] See Elton, Gruber and Blake (2001) and Fama and French (2010) for a discussion of the biases inherent in CRSP mutual fund returns prior to 1984.

[47] Aggregate portfolio characteristics such as return, expense ratio, load and turnover are measured as the net asset value weighted mean of fund share class values. Portfolio total net assets are the sum of share class total net assets. Portfolio age is the age of the oldest fund share class, measured from the date it first appears in CRSP.

[48] Analyses have been conducted using alternative cutoffs of 5 and 10 million dollars, and similar results are found.

returns (requiring a minimum of 11 non-missing returns).[49] Factor loadings from either the single-(CAPM), three- (Fama French), or four- (Carhart) factor models are then used to calculate alphas for that month, where alphas are measured as the difference between the realized excess return and the expected return estimated by multiplying factor loadings by realized factors. The models used for risk adjustment are reported below in equations 7, 8 and 9, respectively:[50]

$$RETRF_i = \alpha_i + \beta_{i,M} MKTRF_t + \varepsilon_{it} \tag{7}$$

$$RETRF_i = \alpha_i + \beta_{i,M} MKTRF_t + \beta_{i,S} SMB_t + \beta_{i,H} HML_t + \varepsilon_{it} \tag{8}$$

$$RETRF_i = \alpha_i + \beta_{i,M} MKTRF_t + \beta_{i,S} SMB_t + \beta_{i,H} HML_t + \beta_{i,U} UMD_t + \varepsilon_{it} \tag{9}$$

To conduct analyses of fund equity trades I match the sample to the Thomson Reuters S12 database using the MFLINKs file. This provides detailed quarterly information on the holdings of each of the funds in the sample from January 1984 through December 2010.[51] Benchmark characteristics and returns are taken from Russ Wermers' website.[52] Stocks are assigned to benchmark portfolios at the end of every June by sorting them into quintiles first by market capitalization (using NYSE breakpoints),

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[49] Using 12 months of returns to estimate factor loadings in rolling regressions is consistent with prior research such as Brown et al. (1996), Chevalier and Ellison (1997), Dong, Feng and Sadka (2012).

[50] RETRF is the assets excess return over the 30 day t-bill rate. MKTRF is the excess return of the CRSP value weighted index over the 30 day t-bill rate. SMB and HML are the small minus big and high minus low factors described and used in Fama and French (1996). UMD is the momentum factor discussed and used in Carhart (1997). Factors for risk adjustment models are obtained from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[51] Wermers (1999) shows that while funds are required to report only semiannually after 1985, the vast majority of funds choose to report quarterly. In our case, if a fund reports semiannually I apply their reported holdings to the following six months instead of the following three with funds that report quarterly. For a more detailed discussion of matching the CRSP data to Thomson see Daniel et al. (1997) and Alexander et al. (2006).

[52] Benchmark characteristics and portfolio returns are obtained from Russ Wermers' website: http://www.rhsmith.umd.edu/Faculty/rwermers/ftpsite/Dgtw/coverpage.htm For a discussion of their construction see Daniel et al. (1997) and Wermers (2004).

then by industry adjusted book-to-market ratios and finally by the preceding 12 month cumulative returns. This procedure results in 125 portfolios held for July through June of the following year. The benchmark adjusted return for each stock is calculated as the difference between its monthly return and the return of the benchmark portfolio it belongs to. I calculate the characteristic benchmark adjusted return for a mutual fund as the mean adjusted return of all of the stocks it holds monthly weighted by the previous quarter's dollar holdings of each stock. The active share of holdings measure is provided by Antti Petajisto.[53]

My final sample consists of 3,393 distinct funds with 351,480 fund month observations. Table 1 reports the time series means of cross sectional fund characteristic summary statistics. The characteristics are in line with expectations. The mean annual expense ratio is 1.29 percent. Annual turnover is 90.57 percent. Net asset growth is 10.74 percent. An interesting statistic is the reported management fee. Unfortunately, the management fee is only available in CRSP from 1998 through 2010. However, during that time period the management fee, at 0.72 percent, accounts for only 56.86 percent of the total expense ratio.[54] A substantial portion of the expense ratio is not compensating the manager for active management. Also of importance are the cross-sectional correlations of fund characteristics with the expense ratio reported in the far right column. All are significantly correlated with expense ratios, suggesting it is important to control for fund characteristics when analyzing the relation between expense ratios and returns.

[53] The active share measure (Petajisto (2010), Cremers and Petajisto (2009)) is downloaded from Antti Petajisto's website: http://www.petajisto.net/data.html

[54] From 1998 through 2010 the mean expense ratio is 1.34 percent.

4. Results

4.1. Expense Ratios and Gross Returns

I begin my analysis with the univariate cross-sectional regression specification used by Gil-Bazo and Ruiz-Verdu (2009). As in their study, I find a negative relation between risk-adjusted gross returns and expense ratios. As reported in Table 2, regressing four-factor gross alphas on one-twelfth the prior year's total expense ratio produces a statistically significant coefficient of -0.32. This coefficient is smaller in absolute terms than the -1.41 found by Gil-Bazo and Ruiz-Verdu (2009).[55] However, it still suggests the same puzzling negative relation. One difference between their analysis and mine is that I also examine raw gross returns. Regressing raw gross returns on the prior year's total expense ratio produces a positive, though statistically insignificant, coefficient of 0.31. While this finding is not the one-to-one positive relation predicted by Berk and Green (2004), it does contradict the puzzling negative relation suggested by Gil-Bazo and Ruiz-Verdu (2009).

I next use portfolio sorting to examine how expenses are related to both returns and other fund characteristics. There are some advantages to portfolio sorting. It can identify non-linearity in a relation, doesn't require distributional assumptions, and allows for examination of how the variable of interest relates to other potentially important variables. Table 3 reports the equal weighted mean characteristics of decile fund portfolios formed every December by total expense ratio and held for the following

[55] Gil-Bazo and Ruiz-Verdu (2009), using cross-sectional regressions, find a univariate coefficient of -1.41. However, their sample period (1963-2006) differs from this study (1984-2010). Applying this same analysis to my sample stretched back to 1963 and regressing four-factor alphas on one-twelfth the lagged expense ratio produces a coefficient of -0.99 and a *p*-value of less than 0.01, which is much closer to their findings.

twelve months. Panel A reports the raw and risk-adjusted gross returns for each decile, as well as the difference between the highest and lowest expense portfolios.[56] The first column reports raw gross returns while the other three report the intercept (alpha) from time series regressions of excess gross returns on the single-, three- and four-factor models as defined in Equations (7), (8), and (9) . The top expense ratio decile outperforms the bottom decile by as much as 14 basis points per month (for three-factor alphas, a statistically significant 9 basis points). These results provide additional evidence contradicting the puzzle found by Gil-Bazo and Ruiz-Verdu (2009).

Panel B of Table 3 provides evidence which reinforces the strong correlation between expense ratios and other fund characteristics found in Table 1. Expense ratios are strongly related to fund total net assets, turnover, and age. The lowest expense ratio funds are considerably larger (by 3.6 billion dollars) than the highest expense ratio funds, have less than half the turnover (50.38 percent versus 128.59 percent) and are twice the age (18 versus 9 years). These correlations complicate the relation between expense ratios and returns, as there is evidence each of these three characteristics also impact returns (Chen et al. (2004), Carhart (1997) and Chevalier and Ellison (1999)).

Berk and Green's prediction of a positive relation between fees and gross returns stems from the assumption that investors allocate capital to mutual funds based solely on their abnormal performance (cash inflows for positive returns, cash outflows for negative returns). However, Sirri and Tufano (1998) finds that investors are concerned with other fund characteristics besides performance (i.e. total net assets and family net assets) when allocating capital. Since prior literature suggests that many fund characteristics impact

[56] Returns weighted by fund total net assets provide similar results, though their alphas are predominately negative.

returns and that investors actively seek out many of those characteristics when allocating capital, it is important to examine the incremental relation between expenses and gross returns while holding other characteristics constant.

Therefore, Table 4 reports the coefficients to regressions of raw and risk-adjusted gross returns on the prior year's expense ratio and other fund characteristics.[57] These multivariate results reveal a very different picture of the expense ratio and return relation. Again, using raw gross returns there is a positive but insignificant relation between expense ratios and returns (0.72). However, using risk-adjusted returns I find a statistically and economically strong positive relation. Regressing three-factor (four-factor) gross alphas on expense ratios reveals a positive 1.22 (0.88) coefficient. These findings are in sharp contrast to both my univariate relation of -0.32 and the -1.41 coefficient found by Gil-Bazo and Ruiz-Verdu (2009).

Overall, I draw two conclusions from these results. First, the relation between expense ratios and gross returns does not appear to be negative. While univariate regressions using risk-adjusted returns suggest a negative relation, regressions with raw returns and portfolio sorting suggest a weakly positive relation. While not perfectly in line with Berk and Green (2004), they do contradict the puzzle identified in Gil-Bazo and Ruiz-Verdu (2009). Second, controlling for fund characteristics known to relate to returns, there is a strong positive relation between expense ratios and gross returns, as predicted by Berk and Green (2004).

[57] Controls included are: prior month's logged total net assets, prior month's logged family net assets, prior year's mean holdings liquidity (Amihud measure), prior year's turnover ratio, the total net asset flow over the prior 12 months, the prior year's maximum load (of front and rear load), the prior year's age (in years) of the oldest share class in the fund (since the share class was first reported in CRSP) and the cumulative raw gross return of the fund over the prior 12 months.

4.2. Management Fees and Gross Returns

The summary statistics of expense ratio deciles reported in Panel B of Table 3 reveal the motivation for examining management fees separately from expense ratios. While expense ratios are positively correlated with management fees (a 0.60 correlation), that correlation is not perfect. For example, the highest expense ratio decile charges an expense ratio that is 1.94 times larger than their management fee. The lowest decile, however, has an expense ratio that is only 1.32 times larger. So not only are management fees the actual compensation managers receive for their ability, but those fees are not perfectly correlated with the expense ratio the fund charges. The result is that management fees may have a stronger or weaker relation with gross returns, and should be tested separately from expense ratios.

I therefore separately examine the relation between management fees and gross returns, starting with portfolio sorting. I sort funds into portfolios each December by management fee and hold them for the following year. Table 5 reports the equal weighted raw and risk-adjusted gross returns to management fee deciles and provides some evidence of a positive relation with gross returns. Raw (single-factor alphas) for the top management fee decile are a significant 26 (22) basis points higher per month than the bottom decile. However, when looking at three- and four-factor alphas the difference drops to 3 basis points. Like with the expense ratio sorting analysis, this isn't strong evidence of a positive relation. Importantly, though, the results are far from puzzling.

Cross-sectional regressions reveal a strong positive relation between management fees and gross returns, both with and without controls. Panel A of Table 6 reports the results from regressing raw and risk-adjusted gross returns on one twelfth the prior year's

management fee. Regressing raw (single-factor adjusted) gross returns on management fees produces a coefficient of 4.65 (3.15). The magnitude of the coefficient shrinks as more factors are added to the risk adjustment model, but remains positive. Inclusion of control variables in Panel B of Table 5 shows a statistically and economically stronger relation. Use of three (four)-factor adjusted gross returns produces a strongly significant coefficient of 1.72 (1.51). Producing coefficients greater than 1, these results show that an increase in management fees is associated with an increase in gross returns greater than the increase in fees.

Overall, the analysis of management fees reveals a consistent and substantially positive relation with gross returns. The relation is robust to empirical method, risk-adjustment and fund characteristic controls. Coupled with the results analyzing expense ratios in the prior section, this is strong evidence that, contrary to Gil-Bazo and Ruiz-Verdu (2009), investors are rationally paying higher prices for higher gross fund performance.

4.3. Trading Skill

While theory predicts a positive relation between fees and gross returns, it also predicts a positive relation between fees and skill. Returns to manager skill may not fully influence fund returns due to trading costs (Berk and Green (2004)). However, that does not invalidate the importance of knowing whether manager skill exists and whether funds with higher fees have managers with more skill. As previously discussed, the Berk and Green (2004) model predicts a positive relation between fees and skill.[58] I therefore examine two proxies of fund skill: active share of holdings and trading skill.

[58] This assertion assumes either a quadratic utility function or other conditions given in Appendix 1.

First, looking at the active share of holdings (Cremers and Petajisto (2009)) I find a strong relation between active share and both expense ratios and management fees. Cremers and Petajisto (2009) find that the deviation of fund holdings (active share) from their closest benchmark is positively related to future fund returns and the persistence of fund returns, interpreting this active share as a proxy for skill. Panel A of Table 7 reports the equal weighted active share of decile fund portfolios formed either on the prior year's expense ratio (first column) or management fee (second column). The lowest expense (management fee) decile has a mean active share of 57.54 (46.28) percent while the highest decile has an active share of 83.16 (88.54). These differences are both statistically and economically substantial. Fund which charge higher fees actively manage a considerably larger portion of their portfolios than funds with lower fees. To the extent active share is a proxy of manager skill these results suggest funds with higher fees have more skill.

Second, I examine the returns to stocks bought and sold by mutual funds to determine whether higher fee funds have more trading skill (Chen et al. (2000)). Every quarter I identify the stocks purchased and sold by each mutual fund. I then measure the dollar value-weighted mean return to stocks purchased (buy return) and stocks sold (sell return) for each fund. The difference between a fund's buy return and sell return is its trading skill. Panel B of Table 7 reports the equal weighted mean buy, sell and buy minus sell (trading skill) returns to portfolios formed every December by reported total expense ratio, for both raw and DGTW adjusted returns. The top expense ratio decile has slightly higher buy returns than the bottom decile (by 11 raw and 8 risk adjusted basis points) and slightly lower sell returns (by -9 raw and -12 risk-adjusted basis points). However, while

these directions suggest trading skill (buying stocks which will outperform and selling stocks which will underperform), neither difference is statistically significant.

Of primary importance is trading skill (buy minus sell returns). The low expense ratio decile has negative buy minus sell returns of -3 (-4) raw (risk adjusted) basis points, showing that the stocks they sell actually outperform the stocks they buy. This suggests low expense ratio funds possess no trading skill. The top expense ratio decile has positive trading skill of 18 basis points, showing the stocks they buy outperform the stocks they sell by 18 basis points per month. The difference in trading skill between low and high expense ratio funds is a statistically significant 21 (22) raw (risk-adjusted) basis points per month. Consistent with Berk and Green (2004), this evidence suggests that funds with higher expense ratios have managers which possess more stock selection skill.

Panel C of Table 7 conducts the same analysis on portfolios formed every December by fund management fees. While the results suggest a similar conclusion, that high management fees are associated with more trading skill, there are two distinct differences. The first is that high management fee funds appear to be substantially better at buying stocks that low management fee funds. The tenth (ninth) decile has raw buy returns 40 (49) basis points higher than the bottom decile. Risk adjusted, the difference is a smaller but still substantial 13 (24) basis points. Second, there appears to be no statistical difference in sell returns between high and low fee funds, suggesting high management fee funds are not better at choosing which stocks to sell.

Turning to trading skill, high management fees are associated with higher buy minus sell returns. The bottom management fee decile has buy returns that underperform sell returns by -21 (-11) raw (risk adjusted) basis points. While the top management fee

decile has moderate returns to trades of 2 basis points, the ninth decile shows evidence of substantial trading skill, as buys returns are 26 (17) raw (risk adjusted) basis points above sell returns. The result is that the top management fee decile has returns to trades that are not statistically higher than the bottom decile. However, the ninth management fee decile has returns to trades 47 (28) raw (risk adjusted) basis points higher than the bottom decile.[59] While this evidence is not as strong as with expense ratios, it still suggests that funds which pay a higher price for active management are getting higher manager skill.

5. Conclusion

Theory predicts a positive relation between the price charged for active management and managerial ability (Berk and Green (2004)). However, recent empirical research suggests that the relation may be non-existent (Chen et al. (2004)) or even negative (Gil-Bazo and Ruiz-Verdu (2009)). The purpose of this paper is to clarify previous puzzling empirical findings by thoroughly examining the relationship between the price of active management and fund performance.

In contrast to the prior literature, I find several results which provide strong evidence of a positive relation between fund fees and fund performance. First, I find that the previously established negative relation between expense ratios and gross returns is not robust to controls. In a multivariate setting which controls for other fund characteristics I find the relation between expense ratios and gross returns is statistically and economically positive. Second, I examine the fee investors pay which directly compensates managers. I find a strong positive univariate and multivariate relation

[59] If I sort funds into quintile portfolios, instead of decile portfolios, I find a statistically significant positive difference between the trading skill of the top and bottom management fee portfolios. However, decile portfolio results are reported to provide consistency with prior analyses.

between management fees and gross returns. Funds with high management fees have gross returns as much as 26 basis points a month higher than low fee funds. Third, as the Berk and Green (2004) model also predicts a positive relation between fess and manager skill, I extend my analysis to two proxies of skill. I find that funds with high expense ratios and manager fees have higher active share (Cremers and Petajisto (2009)) and possess trading skill (buy returns minus sell returns) as much as 47 basis points per month higher than low expense/fee funds.

Overall, I find the relation between price and performance in the mutual fund industry to not be as puzzling as suggested by Gil-Bazo and Ruiz-Verdu (2009) and is, in fact, very consistent with the theoretical predictions of Berk and Green (2004). My findings strongly suggest a positive relation between the price charged for active management and fund performance.

Appendix 1

Berk and Green (2004) posits that fees are a function of skill and trading costs and managers will grow the fund to the point that marginal costs equal skill:

$$f_i = \alpha_i - \frac{C_i(q_i(\alpha_i))}{q_i(\alpha_i)} \tag{A1}$$

$$\alpha_i = c_i'(q_i(\alpha_i)) \tag{A2}$$

To ensure decreasing returns to scale on assets under management they also assume $c_i'(q_i(\alpha_i)) > 0$ and $c_i''(q_i(\alpha_i)) > 0$. I can therefore apply any exponential cost function with $k > 1$:

$$c_i\big(q_i(\alpha_i)\big) = bq_i(\alpha_i)^k \tag{A3}$$

Assuming that fund managers cannot borrow to increase assets under management, equations (A2) and (A3) imply

$$q_i(\alpha_i) = \left(\frac{\alpha_i}{kb}\right)^{1/k-1} \tag{A4}$$

Equations (A3) and (A4) can be put back into (A1) to give fees (f_i) solely as a function of skill (α_i):

$$f_i = \alpha_i - \frac{\alpha_i}{k} \tag{A5}$$

which gives a partial differential of fees (f_i) with respect to skill (α_i) of

$$\frac{\partial f_i}{\partial \alpha_i} = 1 - \frac{b^{k-2}}{k} \tag{A6}$$

So, for any k^{th} exponential cost function the partial derivative of fees (f_i) with respect to skill (α_i) is positive as long as

$$1 > \frac{b^{k-2}}{k} \tag{A7}$$

Appendix 2

I begin with all fund share classes in the CRSP Mutual Fund Database with Lipper objective codes which suggest an investment focus of growth (ELCC, G, LCCE, LCGE, LCVE, MLCE, MLGE, MLVE, SESE), growth and income (EI, EIEI, GI, I), small capitalization (MC, MCCE, MCGE, MCVE, SCCE, SCGE, SCVE, SG) and aggressive growth (CA, MR) or Weisenberger objective codes of growth (G), growth and income (G-I, GCI), small capitalization (SCG), and aggressive growth (AGG, MCG). I also include any fund share class with an investment objective code in the Thomson CDA/Spectrum Database of aggressive growth (2), growth (3), or growth and income (4). This process removes all funds with bond, mixed, derivatives, leverage, emerging markets or international investment objectives.

I then remove fund share classes flagged as either index or institutional by CRSP. As the index flag variable is only accurate for funds existing after June 2008 I remove any fund with the following character strings in their name: INDEX, IDX, IX, INDX, NASDAQ, DOW, MKT, DG, S&P, 500, BARRA. As the institutional class flag is only accurate for funds existing after December 1999 I remove any fund with the following character strings in their name: INSTITUTIONAL, CLASS Y, CLASS I. To reduce the influence of mutual funds with foreign investments I also remove any fund with the following character strings in their name: DEVEL, INTERN, EMERG, EM, EMG, MULTI, PROFUNDS, INC, BHH, RYDEX, SCUDDER, WESTERN ASSET.

Fund share classes are aggregated into fund level portfolios by either matching their name reported in CRSP (stripped of share class identifier) or matching their holdings portfolios with MFLINKs. Aggregate fund characteristics are measured as either

the total net asset value weighted means of share class characteristics (net return, expense ratio, turnover, loads, and asset flow), the sum of share class characteristics (total net assets) or, in the case of age, the oldest share class in the fund. As new funds are often subsidized by their fund families (incubation bias, Evans (2010)) I include funds only once their total aggregate portfolio total net assets exceed 15 million dollars. Also, as a significant portion of funds report only annual earnings prior to 1984 (Elton, Gruber and Blake (2001)) I exclude fund observations prior to 1984.

Funds are then matched to their equity holdings in the Thomson CDA/Spectrum database using MFLINKs. In order for a fund observation to be included in my final sample it must have a return, total net assets and expense ratio reported in CRSP. My final sample consists of 3,393 funds and 351,480 fund month observations.

Table 1

The sample is constructed from all diversified domestic equity funds reported in the CRSP Mutual Fund Survivorship-Bias Free database from 1984 through 2010 excluding index and institutional funds, aggregated at fund portfolio level. Gross returns are calculated as net returns plus one twelfth of the fund's most recently reported expense ratio. Maximum load is the sum of the fund's largest front and rear end loads. Fund TNA is the fund's total net assets reported in millions of dollars. Family TNA is the sum of all total net assets for all funds in a given fund family. Net Asset Growth is the annual change in Fund TNA adjusted for annual returns and is Winsorized at the 1st and 99th percentiles. Multiple share classes of the same fund are aggregated. In those instances the fund's return, expense ratio, loads, asset flow and turnover are calculated as the value weighted average of all the fund's share classes, fund age is the number of years since the oldest share class was first reported in CRSP and the fund's total net assets are the sum of the share class's assets. Reported below are the time series averages of equal weighted cross sectional averages of fund characteristics. Number of funds is the mean of the number of funds in each month of our sample. Growth Funds, Growth and Income Funds, Small Company Growth Funds and Aggressive Growth Funds are the mean monthly percentages of funds belonging to those investment objective classifications as defined by Weisenberger and Lipper Objective Codes in CRSP and Investment Objective Code in the Thomson Reuters S12 database.

Fund Characteristics	Mean	Median	Std	Corr w/ Exp
Expense Ratio	1.29%	1.33%	0.13%	
Management Fee	0.72%	0.73%	0.03%	60.22%***
12b1 Fee	0.37%	0.40%	0.11%	44.19%***
Maximum Load	5.13%	4.61%	1.01%	-4.98%***
Turnover	90.57%	86.25%	115.65%	21.09%***
Net Asset Growth	10.74%	15.62%	29.81%	-1.28%***
Fund TNA ($mill)	901	948	475	-21.34%***
Family TNA ($mill)	35,260	29,983	30,456	-6.10%***
Age (years)	12	12	2	-21.00%***
Number of Funds	1,004	1,136	549	
Growth Objective	59.57%	59.77%	5.41%	
Growth and Income Objective	23.23%	22.02%	4.35%	
Small Company Growth Objective	5.42%	2.28%	5.92%	
Aggressive Growth Objective	11.78%	10.17%	4.08%	

Table 2

Gross raw and risk adjusted returns are regressed on expense ratios. Gross returns are calculated as net returns plus one twelfth of the fund's most recently reported expense ratio. Separate Fama-MacBeth regressions are run using single-factor (CAPM), three-factor (Fama and French (1993)), and four-factor (Carhart (1997)) risk-adjusted returns generated from 12 month rolling regressions.

	Gross Returns		Single Factor		Three Factor		Four Factor	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Exp_{t-1}	0.31	(0.32)	-0.54	(-2.68)	-0.45	(-2.16)	-0.32	(-2.25)
Adjusted R^2	2.87		1.97		0.82		0.68	

Table 3

Summary statistics of portfolios sorted by expense ratios. Gross returns are calculated as net returns plus one twelfth of the fund's most recently reported expense ratio. At the end of every December funds are sorted into decile portfolios based upon the last reported expense ratio and held for the entire following year. Mean equal weighted portfolio monthly gross returns are used to calculate single-factor (CAPM), three-factor (Fama-French), and four-factor (Carhart) risk-adjusted returns. Panel A reports the time series average of the monthly gross and risk adjusted equity returns for each expense decile portfolio. The bottom two rows report the time series average of the cross sectional difference between the tenth (highest) and first (lowest) deciles and the associated t-statistic (in parentheses) for the null hypothesis that the difference is zero. Panel B reports the time series averages of the equal weighted cross sectional means of fund characteristics for each expense decile. Expense Ratio, Max Load, Fund TNA ($mill), Turnover and Age (year) are as defined in Table 1.

Panel A: Returns to Expense Deciles

	Gross Return	Single Factor	Three Factor	Four Factor
(Low) 1	0.94%	0.12%	0.09%	0.08%
2	1.06%	0.30%	0.29%	0.21%
3	0.93%	0.05%	0.04%	0.05%
4	0.91%	0.08%	0.03%	0.03%
5	0.90%	0.00%	-0.01%	-0.03%
6	0.99%	0.09%	0.07%	0.07%
7	0.94%	0.06%	0.05%	0.03%
8	0.97%	0.05%	0.05%	0.04%
9	1.04%	0.11%	0.11%	0.09%
(High) 10	1.08%	0.16%	0.18%	0.15%
10-1	0.14%	0.04%	0.09%	0.06%
t-statistic	(1.50)	(0.52)	(1.85)	(1.19)

Panel B: Fund Characteristics by Expense Decile

	Exp Ratio	Mgmt Fee	Fund TNA	Max Load	Turnover	Age
(Low) 1	0.49%	0.37%	3,864	1.84%	50.38%	18
2	0.82%	0.77%	1,322	3.83%	72.52%	25
3	0.95%	0.83%	1,014	2.84%	80.49%	18
4	1.07%	0.90%	846	2.38%	82.73%	17
5	1.17%	0.95%	687	2.80%	87.23%	15
6	1.27%	0.94%	630	3.13%	87.91%	13
7	1.40%	0.94%	526	3.79%	96.62%	12
8	1.55%	0.93%	458	3.84%	98.17%	11
9	1.74%	0.99%	339	3.95%	105.91%	9
(High) 10	2.25%	1.16%	217	3.49%	128.59%	9

Table 4

Gross raw and risk adjusted returns are regressed on expense ratios and fund characteristic control variables. Gross returns are calculated as net returns plus one twelfth of the fund's most recently reported expense ratio. Separate Fama-MacBeth regressions are run using single-factor (CAPM), three-factor (Fama and French (1993)), and four-factor (Carhart (1997)) risk-adjusted returns generated from 12 month rolling regressions. Control variables included in the regressions are lagged logged total net assets, logged family total net assets, cumulative annual return, annual turnover, maximum of front and rear loads, age and annual net asset flow as defined in Table 1.

	Gross Returns		Single Factor		Three Factor		Four Factor	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Exp_{t-1}	0.72	(0.53)	1.46	(6.40)	1.22	(7.98)	0.88	(5.50)
$LogTNA_{t-1}$	-0.26	(-1.38)	0.14	(3.14)	-0.08	(-2.14)	-0.15	(-3.58)
$LogFTNA_{t-1}$	0.33	(2.43)	0.03	(1.26)	0.08	(4.22)	0.08	(3.81)
$Amihud_{t-1}$	0.15	(0.07)	1.56	(1.85)	0.37	(0.71)	-0.15	(-0.31)
$Turn_{t-1}$	0.65	(1.43)	-0.13	(-1.59)	-0.07	(-0.86)	-0.19	(-2.85)
$Flow_{t-1}$	-0.35	(-2.99)	0.36	(23.04)	0.24	(21.61)	0.23	(20.69)
$Load_{t-1}$	-0.02	(-1.43)	-0.01	(-7.51)	-0.01	(-3.94)	-0.01	(-2.60)
Age_{t-1}	-0.05	(-1.43)	0.00	(0.79)	0.00	(0.90)	-0.00	(-0.45)
$Return_{t-1}$	0.00	(0.04)	0.36	(8.10)	0.39	(8.12)	0.39	(8.08)
Adjusted R^2	21.85		31.08		24.09		22.10	

Table 5

Portfolio sorting using management fees for the sample period of 1998 through 2010. Gross returns are calculated as net returns plus one twelfth of the fund's most recently reported expense ratio. At the end of every December funds are sorted into decile portfolios based upon the last reported management fee and held for the entire following year. Mean equal weighted portfolio monthly gross returns are used to calculate single-factor (CAPM), three-factor (Fama-French), and four-factor (Carhart) risk-adjusted returns. Reported are the time series average of the monthly gross and risk adjusted equity returns for each management fee decile portfolio. The bottom two rows report the time series average of the cross sectional difference between the tenth (highest) and first (lowest) deciles and the associated *t*-statistic (in parentheses) for the null hypothesis that the difference is zero.

	Gross Return	Single Factor	Three Factor	Four Factor
(Low) 1	0.51%	0.14%	0.12%	0.12%
2	0.50%	0.12%	0.04%	0.04%
3	0.57%	0.17%	0.12%	0.11%
4	0.49%	0.11%	0.09%	0.08%
5	0.60%	0.24%	0.16%	0.16%
6	0.55%	0.15%	0.05%	0.04%
7	0.94%	0.53%	0.38%	0.26%
8	0.68%	0.27%	0.10%	0.08%
9	0.78%	0.37%	0.21%	0.21%
(High) 10	0.77%	0.36%	0.15%	0.15%
10-1	0.26%	0.22%	0.03%	0.03%
t-statistic	(1.64)	(1.72)	(0.71)	(0.66)

Table 6

Gross raw and risk adjusted returns are regressed on management fees and fund characteristic control variables for the sample period of 1998 through 2010. Gross returns are calculated as net returns plus one twelfth of the fund's most recently reported expense ratio. Separate Fama-MacBeth regressions are run using single-factor (CAPM), three-factor (Fama and French (1993)), and four-factor (Carhart (1997)) risk-adjusted returns generated from 12 month rolling regressions. Panel A reports univariate regressions. Panel B is multivariate, where control variables included in the regressions are lagged logged total net assets, logged family total net assets, cumulative annual return, annual turnover, maximum of front and rear loads, age, and annual net asset flow as defined in Table 1.

	Raw Returns		Single Factor		Three Factor		Four Factor	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: Univariate								
$MFee_{t-1}$	4.65	(1.98)	3.15	(5.44)	1.00	(2.43)	0.57	(1.54)
Adjusted R^2	2.98		2.02		0.96		1.04	
Panel B: Multivariate								
$MFee_{t-1}$	2.51	(1.37)	3.05	(7.63)	1.72	(5.37)	1.51	(4.53)
$LogTNA_{t-1}$	-0.30	(-1.31)	0.16	(2.33)	0.20	(4.97)	0.14	(3.42)
$LogFTNA_{t-1}$	0.53	(2.04)	0.15	(5.87)	-0.03	(-1.35)	0.00	(0.43)
$Amihud_{t-1}$	0.66	(1.70)	0.47	(2.95)	0.25	(2.67)	0.14	(1.62)
$Turn_{t-1}$	0.15	(1.69)	0.02	(0.89)	-0.01	(-0.50)	0.00	(0.17)
$Flow_{t-1}$	-0.43	(-1.91)	0.32	(18.22)	0.24	(16.80)	0.22	(15.89)
$Load_{t-1}$	-0.03	(-1.57)	-0.94	(-5.69)	-0.61	(-3.82)	-0.25	(-1.46)
Age_{t-1}	-0.01	(-1.25)	-0.02	(-3.59)	0.00	(0.10)	-0.00	(-1.29)
$Return_{t-1}$	0.30	(2.42)	0.28	(5.49)	0.17	(4.86)	0.16	(4.85)
Adjusted R^2	22.85		36.99		27.97		25.15	

Table 7

Analysis of fund trades for portfolios sorted by either the prior year's expense ratio or management fees. Abnormal equity returns are calculated in accordance with Daniel, Grinblatt, Titman and Wermers (1997), matching stocks to their respective size, book-to-market and momentum quintile portfolios every June and calculating their abnormal returns as the difference between their monthly raw return and the return of their matching characteristic-based portfolio. Individual stocks and their returns (both raw and abnormal) are matched to each fund in our sample using the Thompson Reuters S12 fund holdings database, where a fund's abnormal return is the average abnormal return of the stocks it holds weighted by the dollar holding of the stock in the prior report. Panel A reports equal weighted monthly mean of fund holding's active share of portfolios formed either by the prior year's expense ratio or management fee. Panel B reports equal and value weighted monthly returns for decile portfolios formed using the prior year's reported expense ratio for equities bought, sold, and the difference in returns between stocks bought and sold for the sample period of 1984 through 2010. The bottom four rows report the average of the difference between the first (lowest) and ninth (second highest) or first (lowest) and tenth (highest) deciles and the associated t-statistic (in parentheses) for the null hypothesis that the difference is zero. Panel C reports the same results to decile portfolios sorted by the prior year's management fee using the sample period of 1998 through 2010.

Panel A: Active Share of Holdings

	Expense Ratio	Management Fee
(Low) 1	57.54%	46.28%
2	68.69%	71.38%
3	75.51%	70.48%
4	78.88%	73.29%
5	80.14%	63.51%
6	81.21%	75.23%
7	82.33%	78.16%
8	81.54%	80.57%
9	84.38%	85.61%
(High) 10	83.16%	88.54%
10-1	25.68%	42.27%
t-statistic	(36.41)	(78.96)

	Raw Returns			DGTW Returns		
	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell
Panel B: Expense Deciles						
(Low) 1	0.97%	0.99%	-0.03%	0.00%	0.02%	-0.04%
2	0.95%	0.89%	0.05%	-0.06%	-0.07%	-0.01%
3	0.96%	0.87%	0.10%	-0.04%	-0.11%	0.09%
4	0.98%	0.89%	0.08%	-0.06%	-0.12%	0.05%
5	0.93%	0.80%	0.13%	-0.07%	-0.19%	0.11%
6	0.96%	0.88%	0.06%	-0.04%	-0.08%	0.03%
7	0.98%	0.76%	0.22%	-0.01%	-0.22%	0.22%
8	0.94%	0.87%	0.09%	-0.04%	-0.12%	0.09%
9	1.12%	0.83%	0.29%	0.12%	-0.15%	0.26%
(High) 10	1.08%	0.90%	0.18%	0.08%	-0.10%	0.18%
9-1	0.14%	-0.15%	0.32%	0.11%	-0.17%	0.30%
t-statistic	(1.49)	(-1.57)	(3.14)	(1.58)	(-2.13)	(3.36)
10-1	0.11%	-0.09%	0.21%	0.08%	-0.12%	0.22%
t-statistic	(1.16)	(-0.90)	(2.59)	(1.19)	(-1.56)	(2.89)
Panel C: Management Fee Deciles						
(Low) 1	0.22%	0.40%	-0.21%	-0.13%	-0.05%	-0.11%
2	0.44%	0.39%	0.03%	0.00%	-0.03%	0.02%
3	0.40%	0.35%	0.05%	-0.02%	-0.06%	0.04%
4	0.41%	0.30%	0.12%	-0.05%	-0.15%	0.11%
5	0.48%	0.45%	-0.02%	0.01%	0.01%	-0.06%
6	0.52%	0.36%	0.16%	0.02%	-0.10%	0.11%
7	0.43%	0.32%	0.12%	-0.07%	-0.17%	0.11%
8	0.56%	0.43%	0.17%	0.02%	-0.01%	0.05%
9	0.71%	0.47%	0.26%	0.11%	-0.05%	0.17%
(High) 10	0.63%	0.61%	0.02%	0.00%	-0.02%	0.02%
9-1	0.49%	0.07%	0.47%	0.24%	0.00%	0.28%
t-statistic	(3.40)	(0.44)	(2.99)	(2.75)	(0.01)	(2.42)
10-1	0.40%	0.21%	0.23%	0.13%	0.02%	0.13%
t-statistic	(2.06)	(0.89)	(1.31)	(1.32)	(0.19)	(0.87)

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