Aalto University
School of Economics

# Do Mutual Funds Time Market Liquidity? A Study On US Mutual Fund Performance

Finance

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Abstract
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DO MUTUAL FUNDS TIME MARKET LIQUIDITY?
A STUDY ON U.S. MUTUAL FUND PERFORMANCE

PURPOSE OF THE STUDY

The purpose of my thesis is to study whether actively managed mutual funds successfully alter market exposure in anticipation of changes in aggregate liquidity. Specifically, I test whether funds increase (decrease) market exposure prior to increases (declines) in liquidity. Furthermore, I investigate whether certain fund characteristics are related to funds' success in timing liquidity. As liquidity has been shown to be positively related to asset returns and negatively related to market volatility, mutual funds could benefit from the ability to predict and time changes in aggregate liquidity. Although market liquidity has been identified as an important risk factor affecting asset returns, it hasn't received much attention in timing literature. My study adds to the so far scarce evidence on mutual funds' liquidity timing ability.

DATA

I use monthly return data on 21,500 actively managed US mutual funds, ranging from January 1980 to December 2010. Fund data come from the CRSP Survivor-Bias-Free US Mutual Fund Database. The sample contains open-ended equity, fixed income and balanced funds. The Sadka (2006) liquidity shock measure and innovations to average stock turnover and trading volume are used to proxy for market liquidity.

RESULTS

My results provide additional evidence that mutual fund managers in fact adjust the level of market exposure prior to changes in aggregate liquidity. The results are surprisingly consistent across all three liquidity measures and hold in a variety of robustness checks. On average, mutual funds increase market exposure by 2.8% to 7.5% prior to a one-standard-deviation increase in market liquidity, depending on the liquidity measure used. Funds with riskier investment strategies outperform more conservative funds in timing ability. Evidence on the relationship between timing ability and fund characteristics is weaker, but it seems that successful timers charge higher fees, have higher fund flow volatility, possibly experience higher flows and and trade less. Fund age and size appear insignificant.

KEYWORDS

Mutual funds, liquidity, market timing, fund performance

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AJOITTAVATKO SIJOITUSRAHASTOT MARKKINALIKVIDITEETTIÄ?
TUTKIMUS AMERIKKALAISESTA RAHASTOMARKKINASTA

TUTKIELMAN TAVOITTEET

Tutkielmani tarkastelee aktiivisesti hoidettujen amerikkalaisten sijoitusrahastojen kykyä ennakoida markkinalikviditeetin muutoksia sijoitustoiminnassaan. Ajoituksen onnistumista estimoin regressiomallilla, joka testaa lisäävätkö (vähentävätkö) rahastot systemaattista riskiään ennen markkinalikviditeetin paranemista (heikkenemistä). Lisäksi tutkin onko ajoituskyvyn ja tiettyjen rahaston ominaisuuksien välillä havaittavissa yhteyttä. Likviditeetin on osoitettu olevan merkittävä sijoitustuottoihin vaikuttava riskitekijä – näin ollen rahastot voivat hyötyä kyvystä ennakoida markkinalikviditeettiä. Vaikka sijoitusrahastojen kykyä ajoittaa markkinatuottoja tai volatiliteettia on tutkittu runsaasti, on markkinalikviditeetti jäänyt vähemmälle huomiolle. Tutkielmani täydentää aihealueen toistaiseksi ohutta empiriaa.

LÄHDEAINEISTO

Tutkielmassani käytän kuukausittaista tuottodataa 21 500 amerikkalaisesta aktiivisesti hoidetusta rahastosta. Otoksen aikaväli on tammikuusta 1980 joulukuuhun 2010. Rahastojen tuottohistoria sekä ominaisuudet on haettu CRSP Survivor-Bias-Free US Mutual Fund -tietokannasta. Rahastodata sisältää sekä osake-, korko- että yhdistelmärahastoja. Markkinalikviditeetin arvioimiseen käytän Sadkan (2006) likviditeettishokkia sekä poikkeamia keskimääräisestä osakkeiden kaupankäyntivolyymista ja kiertonopeudesta.

TULOKSET

Tulokseni osoittavat että keskimäärin rahastot ennakoivat markkinalikviditeettiä ja muuttavat tämän mukaisesti systemaattista riskiään osakemarkkinalla. Tulokset ovat huomattavan yhdenmukaisia likviditeettimittarista riippumatta ja säilyvät muuttumattomina useissa lisätesteissä. Keskimäärin rahastojen osakebeta kasvaa 2,8 - 7,5 prosentilla ennen yhden keskihajonnan suuruista lisäystä markkinalikviditeetissä. Sijoitusstrategialtaan riskisemmät rahastot onnistuvat likviditeettishokkien ajoittamisessa parhaiten. Näyttö rahastojen ominaisuuksien ja ajoituskyvyn suhteesta on tilastolliselta merkittävyydeltään hieman heikompaa, mutta kyvykkään rahastot näyttäisivät olevan kalliimpia, keräävän enemmän nettomerkintöjä, käyvän vähemmän kauppaa ja niiden merkintöjen volatiliteetti on suurempaa.

AVAINSANAT

Sijoitusrahastot, likviditeetti, rahastoperformanssi, markkina-ajoitus

# Contents

# 1 Introduction

An extensive amount of research in finance has focused on mutual funds' ability to time market conditions such as returns and volatility. Something that hasn't yet received as much attention is funds' ability to time liquidity in the financial markets. Cao, Simin and Wang (2010) examine this in a recent paper and find that US equity fund managers demonstrate ability to time market liquidity, i.e. increase (reduce) market exposure in anticipation of more liquid (illiquid) markets. Conflicting evidence is presented in a study by Winter (2011), who uses alternative methodology and concludes that fund managers are unable to time variation in the market liquidity risk factor.

## 1.1 Theoretical Background

Investors expect mutual fund managers to have the expertise to identify and utilize well-performing risk factors, and correspondingly decrease portfolio exposure to market factors that cause poor performance. Market-wide liquidity has a significant impact on mutual fund performance, as recent events in the financial markets have shown. Research in asset pricing has identified aggregate liquidity as an important determinant of stock returns (see e.g. Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). Furthermore, the same equity-based systematic liquidity factors that affect stock returns also seem to affect the pricing of bond returns (e.g. Lin, Wang and Wu, 2011). Decreasing liquidity implies higher required returns for securities that are sensitive to liquidity, and therefore low contemporaneous returns at a time when liquidity decreases. This suggests that mutual fund managers can benefit from the ability to anticipate future changes in market-wide liquidity.

Liquidity is not only a characteristic of individual assets: several studies document observed commonality in liquidity. The fact that asset prices show sensitivity to systematic variation in liquidity has implications for fund management. Chordia, Roll and Subrahmanyam (2000, 2001) are among the first to explore commonality in liquidity. Besides documenting that individual assets' liquidity measures show co-movement, they find that liquidity is asymmetrically related to market returns. That is, systematic liquidity decreases significantly in down markets, but the improvement in liquidity during periods of positive market returns is not as significant. Huberman and Halka (2001) also investigate commonality in liquidity and find that common variation in liquidity is positively correlated with market returns and negatively correlated with market volatility. Several studies follow and arrive at similar conclusions: liquidity measures exhibit commonality across assets and aggregate liquidity varies with market returns and volatility (e.g. Hameed, Kang and Viswanathan, 2010; Domowitz, Hansch and Wang, 2005).

Dong, Feng and Sadka (2011) show that fund performance is significantly linked to the level of the fund's exposure to liquidity risk. They find that funds loading on liquidity risk subsequently outperform those that have lower exposure to market liquidity. Massa and Phalippou (2005) find that mutual funds engage in active liquidity management: they adjust portfolio liquidity with respect to changes in liquidity needs and shocks to market-wide liquidity. Furthermore, Pastor and Stambaugh (2003) find that individual stocks' liquidity betas predict their future liquidity risk – thus skilled fund managers may be able to predict future liquidity conditions.

A simplified example illustrates the concept of liquidity timing considered in my thesis. Consider that funds only hold two assets, cash or stocks. As liquidity is persistent and predicts market returns, fund managers with liquidity timing ability would shift out of cash and into stocks to increase market exposure in anticipation of more liquid markets and higher returns. An opposite shift in asset allocation would be made if the fund manager expected a decrease in aggregate liquidity. Thus, successful liquidity timing managers would increase the fund's systematic risk (market beta) prior to increases in market liquidity, and vice versa.

## 1.2 Research Contribution of My Thesis

Liquidity itself is a multidimensional concept, and covered by a vast amount of research literature, both on the idiosyncratic and systematic aspects. Furthermore, the relationship between systematic liquidity risk and asset returns is intuitively appealing and documented in several studies. Considering this, the existing literature on mutual funds' liquidity timing is surprisingly scarce, and the evidence is mixed. My thesis aims to fill in on this gap. Specifically, I study a relatively large sample of actively managed US mutual funds and test whether funds adjust market exposure prior to changes in aggregate liquidity. All fund data in my study comes from the CRSP Survivor-Bias-Free US Mutual Fund Database and range from January 1980 to December 2010. This time period also contains the very recent financial crisis, which resulted in a wide-spread liquidity squeeze in the financial markets. My methodology follows that of Cao, Simin and Wang (2010), but I include both equity and fixed income funds in my sample and perform additional robustness checks. Furthermore, I use three market liquidity measures that haven't been previously used in liquidity timing studies. The Sadka (2006) liquidity measure is used to proxy for return-reversal related liquidity. Average equity turnover and trading volume estimate trading activity related liquidity.

## 1.3 Overview of Results

The three liquidity measures mostly produce qualitatively similar results on funds' liquidity timing. My results suggest that US mutual funds demonstrate significant positive liquidity timing ability, and that there are cross-sectional differences in liquidity timing with respect to investment strategy and fund characteristics. On average, mutual funds increase exposure by 2.8% to 7.5% in anticipation of a one-standard-deviation increase in aggregate liquidity, depending on the liquidity measure used. I find evidence that liquidity timing ability increases with the riskiness of a fund's investment strategy. The riskiest aggressive growth funds demonstrate the most significant timing ability, followed by growth funds and growth and income funds. Aggressive funds invest more heavily in small companies (Chen, Hong, Huang and Kubik, 2004), for which liquidity risk seems to be especially significant (Amihud, 2002). It seems that funds with more illiquid holdings are the most successful in timing market liquidity.

Furthermore, my data indicates that fund fees and fund flow volatility are positively related to timing ability, whereas fund turnover rate and timing skill show a negative relationship. Fund age is insignificant and evidence on the size relationship is mixed. Liquidity timing funds clearly provide a hedge and are able to charge investors more for this service. For some reason successful liquidity timers trade less, which indicates that liquidity timing does not require very extensive portfolio rotation compared to funds that do not time liquidity. The observed positive relationship between fund flow volatility and timing skill is consistent with the fact that aggressive growth funds have the most volatile fund flows. This is somewhat surprising, considering that volatile flows could complicate the implementation of a fund's investment strategy.

I perform several additional tests and robustness checks. Funds' liquidity timing seems to be a relatively recent phenomenon, as the latter half of the sample demonstrates significantly stronger liquidity timing than the first half. Liquidity timing tests with the Sadka liquidity measure and trading volume also indicate that timing success is strongly driven by periods of market turmoil and extraordinary liquidity conditions. This suggests that fund managers may engage in liquidity timing more actively during liquidity crises, but neglect this aspect during "normal" market conditions.

Controlling for a liquidity risk factor in fund returns does not alter inference about liquidity timing. As for liquidity risk exposure, funds seem to have negative loadings on the liquidity risk premium. Despite the positive correlation between market returns and liquidity and negative correlation between market volatility and liquidity, liquidity timing remains significant after controlling for returns and volatility timing in fund returns. Tests on a sample of index funds indicate that the observed positive liquidity timing isn't simply due to a passive timing effect, which could result from the market betas of assets changing with liquidity.

A potential concern is that large funds' own trading affects market liquidity (e.g. Khandani and Lo, 2009) and thereby creates an artificial impression of liquidity timing. I run liquidity timing tests on several fund size portfolios and conclude that the differences in liquidity timing between large and small funds are negligible when testing with the Sadka liquidity measure and turnover. This is supportive of the observed positive timing ability, as small funds' trades are less likely to affect market liquidity. Trading volume, on the other hand, presents mixed evidence – it is possible that large funds generate a large fraction of aggregate trading volume, which casts a doubt on the reliability of results for this liquidity measure. Finally, I test for the possibility that fund managers merely react to public information of past liquidity levels, instead of predicting future liquidity. The main conclusion is that timing is related to liquidity prediction rather than reacting to past liquidity conditions.

The rest of my thesis is organized as follows. Section 2 presents the most important literature on financial market liquidity and its implications for fund management. Section 3 presents my research hypotheses and Section 4 the data and methods used. The results are presented in Section 5, and Section 6 concludes.

# 2 Literature Review

## 2.1 Previous Fund Timing Studies

Fund managers' ability to predict changing market conditions and adjust exposure to market factors has been a popular research topic in finance literature ever since the 1960s. The earliest fund timing studies focus on the timing of market returns, with with Treynor and Mazuy (1966), Fama (1972) and Jensen (1972) pioneering in this field of study and numerous others following. The most common approach is to test whether funds increase exposure to the market index prior to market advances and vice versa. Of the more recent market timing studies, Jiang, Yao and Yu (2007) use portfolio holdings rather than returns-based measures to measure timing and find evidence of funds' market return timing ability. However, the majority of this literature seems to conclude that no consistent ability of funds to predict and utilize market movements is observable. From an academic point of view, these studies are interesting because identifying funds with market timing ability challenges the efficient market hypothesis. For investors and the public at large, the market timing ability of mutual funds is interesting because of the massive supply of funds offered and investors' quest to find top-performing fund managers.

### *2.1.1 Timing Market Returns*

Treynor and Mazuy (1966) are the first to investigate and present their findings of mutual fund managers' ability to time market returns, i.e. adjust the fund's exposure prior to market advances or declines. They present a methodology that has been subsequently used in numerous timing studies, stating that in the presence of market timing ability, the relationship between a fund's return and the market return is convex. This means that during times of positive market returns, funds ride along or increase systematic risk, whereas during down markets fund's decrease market exposure and outperform the market. Treynor and Mazuy use the performance record of 57 open-ended mutual funds, covering the years 1953-1962, and find no evidence of market timing ability. More specifically, no curvature is found in the relationship between fund returns and market returns. They conclude that an investor in a mutual fund is completely dependent on the fluctuations of the entire market. Fund managers may be able to outperform the market by picking out companies and industries that are underpriced, but they do not show ability to outguess general market movements.

In the early 1970s, theoretical frameworks were developed for evaluating investment portfolios' success in so called micro and macro forecasting. Fama (1972) presents one of the grounding studies in mutual fund's performance measurement. His paper introduces methods for distinguishing between returns from asset picking and returns from timing market movements. Jensen (1972) also develops a model to test for a portfolio manager's forecasting and security selection abilities. Both papers focus on the comparison of the ex post performance of a managed portfolio to the market returns. Still, these two early models are limited in their ability to break down the components of investment performance. Henriksson and Merton (1981) continue along these lines, further developing a model that allows evaluating investment managers' performance by identifying and separating gains from market timing skills and security selection skills without making assumptions about return distributions or price formation in the market. Chang and Lewellen (1984) employ Henriksson and Merton's methodology and conclude that few mutual fund managers display any market timing skills, and that collectively fund managers do not seem to outperform a passive investment strategy. Jagannathan and Korajczyk (1986) continue the investigation of methods to uncover timing ability and show that it is possible to construct portfolios showing artificial timing ability, e.g. by investing in options or levered securities. They claim this could be behind earlier results showing weak or negative timing ability of mutual funds. If funds mainly invest in high quality (i.e. less option-like) securities, this could bias estimates of timing ability downwards. Jagannathan and Korajczyk suggest improvements to previously employed methods to help distinguish between spurious and true timing ability.

Lee and Rahman (1990) continue in the footsteps of Treynor and Mazuy (1966), searching for a convex return relationship between fund and market returns. They study 97 individual funds during 1977-1984 and find some evidence of forecasting ability at the individual fund level. During the 1990s, several studies have focused on this topic and suggested modifications to the methods presented earlier. Edelen (1999) studies funds' timing ability by adding a regressor for fund flows. He finds that after controlling for the effects of fund flow related liquidity trading, no sign of either excess returns or timing ability (negative or positive) is found. This is in contrast to results without fund flow controls, which suggest negative alpha and market timing ability. Bollen and Busse (2001) argue that previous studies on timing suffer from using monthly returns, as decisions about allocation are likely made more frequently for most funds. They use both daily and monthly fund data and find that daily data produces more significant observations about timing ability, whether positive or negative. They conclude that more fund managers possess timing skills than has been documented in previous studies.

More recently, Jiang, Yao and Yu (2007) introduce the use of mutual fund holdings instead of returns to test for timing ability. They find that on average US mutual funds do exhibit positive market timing ability and that successful timers utilize non-public information, have higher industry concentration, larger fund size, and tilt towards small-caps. However, the tests that Jiang, Yao and Yu perform using return data still suggest that on average, funds' timing ability is slightly negative and statistically insignificant. In recent years several market timing studies have focused on markets other than the US, as well as expanded the scope from equity funds to fixed income funds, hedge funds etc. For example Chen, Ferson and Peters (2010) measure the market timing ability of bond fund managers, and find that many funds exhibit some investment timing ability, but on an after-cost basis their performance is negative compared to a passive investment strategy. Chen and Liang (2007) study self-described market timing US hedge funds and find timing ability at both aggregate and individual fund levels. Timing seems especially strong in bear markets and volatile market conditions.

### *2.1.2 Timing Volatility*

Busse (1999) is the first to study whether mutual funds are able to time market volatility, i.e. change market exposure as volatility changes. Busse argues that unlike market returns, market volatility is persistent and therefore easier to predict. Also, fund managers compensation is often related to risk-adjusted returns, and therefore fund managers should be interested in the effects of volatility on their portfolio. Whether risk-adjusted returns can be increased by timing volatility is another question, though. If market returns and volatility are unrelated, fund managers could increase investors' utility by decreasing exposure during times of high volatility. On the opposite, decreasing exposure during high volatility could expose investors to other risks such as interest rate risk. Busse uses daily market and fund data and finds a strong negative relationship between funds' systematic risk levels and market volatility. Furthermore, Busse documents a significant relationship between volatility timing coefficients and investment performance – that is, funds that decrease systematic risk during times of high volatility earn higher risk-adjusted returns. This means that successful volatility timers provide investors with a valuable volatility hedge.

Gomes (2007) builds a model to estimate utility gains from volatility timing and finds that short-run portfolio rebalancing with respect to volatility is beneficial even after transaction costs. Giambona and Golec (2009) continue the study of Busse (1999) and estimate that about 60 per cent of US funds included in their sample time volatility counter-cyclically, i.e. hedge volatility. They estimate that aggressiveness (pro-cyclical volatility timing) improves fund performance, but this effect decreases with the magnitude of the timing. Although Marquering and Verbeek (2004) do not study funds specifically, their study is interesting as it also shows that successful volatility timing is beneficial for investors, even after transaction costs.

Although mutual funds' ability to time market returns and volatility has received plenty of attention in finance research, there are only few studies which investigate whether funds adjust their market exposure with respect to changes in aggregate market liquidity. The observation that liquidity seems to be a priced risk factor motivates further investigation of the topic.

### *2.1.3 Timing Liquidity*

My study continues that of Cao, Simin and Wang (2010), CSW hereafter, which focuses on the ability of mutual fund managers to time market-wide liquidity. CSW use the Pastor-Stambaugh (2003) and Amihud (2002) liquidity measures to estimate monthly market-wide liquidity and then estimate the sensitivity of excess returns to liquidity for each fund. They also use controls for return timing and volatility timing in their regression model to ensure that volatility and return timing don't simply manifest themselves in the liquidity timing coefficients. CSW find significant evidence indicating that fund managers are in fact able to change market exposure in response to future liquidity conditions. Specifically, fund managers increase (decrease) exposure in anticipation of increased (decreased) market-wide liquidity. On average, fund managers would seem to increase (reduce) portfolio exposure by approximately 4 %, when they expect a one standard-deviation increase (decrease) in aggregate liquidity. CSW also find that aggressive growth funds demonstrate the most significant liquidity timing ability, whereas income funds' timing ability is weaker than other funds'. Cheng, Hong, Huang and Kubik (2004) show that aggressive funds tend to invest more heavily towards small-cap stocks, which are less liquid. Thus the results imply that funds holding less liquid assets are more successful in liquidity timing. Furthermore, timing coefficients are weakest for non-surviving funds; liquidity timers have longer histories and trade more actively. The CSW study suggests that market liquidity plays an important role in the allocation decisions of mutual fund managers and in the time variation of mutual fund betas. The difference in risk-adjusted return between top and bottom liquidity timing funds according to their study is approximately 2% annually during the 1974 to 2008 period.

The empirical results of CSW suggest that the observed liquidity effect is not dependent on the use of a particular liquidity measure (both Pastor Stambaugh and Amihud produce similar results). Also, liquidity timing coefficients are not significant for index funds, which suggests that the documented liquidity timing ability is not only due to a passive timing effect, e.g. stock betas increasing with liquidity. Additional robustness to the results is provided by the use of a liquidity risk factor (Pastor and Stambaugh, 2003). Previous studies suggest that liquidity risk is important in driving stock returns, but adding it to the Carhart four-factor model doesn't affect the significance of liquidity timing coefficients in CSW's study. Sub-period tests reveal that the observed liquidity timing ability weakens in time. This would be consistent with the rational expectations model of Berk and Green (2004), who model how investors' chase for returns in a competitive market wipes out excess returns. CSW also use a bootstrap approach to investigate liquidity timing ability at the individual fund level, and find evidence that the observed timing ability isn't simply attributed to luck. Finally, to investigate what kind of fund characteristics are associated with liquidity timing ability, CSW regress the liquidity timing coefficients of funds on fund age, size, expense ratio, turnover rate and fund flow. Results suggest liquidity timing funds are older and have a higher turnover rate.

Findings like this are interesting considering that mutual funds are usually very restricted in their trading strategies and investment policies. For example, most traditional mutual funds are only allowed take long positions, and many have strictly defined rules about the portion of assets under management that have to be invested, despite the market situation. Therefore one would assume that mutual funds are fairly restricted in their ability to time the market in any way, even if they tried to. Hedge funds, on the other hand, often utilize strategies such as short selling and leverage, and have less restricting requirements about investment levels. Consistent with this remark, Cao, Chen, Liang and Lo (2011) perform similar analysis to CSW but use hedge fund data, and find much stronger positive liquidity timing analysis.

In a very recent research paper, Winter (2011) uses an alternative methodology to analyze mutual funds' timing skill, but finds no evidence of successful timing. Specifically, she uses a Kalman filter procedure to estimate daily time-varying risk exposures, and then studies whether mutual funds and hedge funds are able to time the liquidity risk factor. Winter's mutual fund data ranges from 2002 to 2009. She concludes that fund managers are not successful in incorporating information or expectations about past, current or future market liquidity risk into portfolio management decisions.

The evidence on mutual funds' liquidity timing so far is scarce and mixed. My thesis focuses on conventional mutual funds and should shed more light on the recent findings of mutual funds' liquidity risk exposure.

## 2.2 Defining Liquidity

Liquidity in the financial markets is most often defined as the ability to trade an asset quickly and at low cost without significantly moving the price of the asset. Black (1971) elaborates on this, pointing out that liquid markets should not be interpreted as being able to trade large quantities of an asset without moving the price. This is because generally an investor will not buy or sell large quantities unless they believe to possess information that will substantially affect the future price of the asset. If this is the case, other market participants will not trade without adjusting the price accordingly. Black lists four factors defining a liquid market:

1) There are always bid and ask prices for an investor who wants to trade small amounts of an asset immediately.
2) The bid-ask spread is small.
3) Large quantities of an asset can be sold over a long time period at prices that are on average close to the current price, assuming no special information.
4) Large blocks can be bought or sold immediately, but at a price that reflects the size of the trade.

In an early paper, Demsetz (1968) defines liquidity as the cost of immediate execution of a trade. He notes that this cost varies for different assets and that increased liquidity (trading activity) can bring this cost down. Lippman and McCall (1986) define liquidity as the time it takes to optimally exchange an asset into money.

In asset pricing theory, a basic assumption is that a security whose lowest returns tend to coincide with unfavorable shifts in other factors affecting the investors overall welfare must offer additional compensation to the investor for holding that security (Pastor and Stambaugh, 2003). Liquidity would seem to be such a priced state variable.

So what drives liquidity in the financial markets? There are two tranches in finance literature that offer explanations to changes in the level of liquidity for an asset. First of all, trading financial assets usually incurs so called real friction, as defined by Stoll (2000). Real friction can be interpreted as trading costs that reflect the payment for services provided by the market maker. The supply of immediacy in trading requires real economic resources such as labor and capital. Additionally, market makers assume unwanted inventory risk for which they require compensation. Market power is also a source of real friction in trading financial assets: dealers with market power will increase the required compensation relative to their costs of providing immediacy.

The second tranche in finance literature uses informational arguments to define liquidity. Copeland and Galai (1983), Glosten and Milgrom (1985) and Kyle (1985) are among the first papers to formulate this idea of trading friction. Under this view, the costs of trading result from informational asymmetry between the buyer and seller of an asset. The bid-ask spread would thus reflect the value of information lost to better informed traders: informed traders will buy at the ask price if they have information justifying a higher price, and sell at the bid if they have information justifying a lower price. Thus informed traders gain at the expense of suppliers of liquidity if the information is later reflected in the asset’s price. Bagehot (pseudonym for Treynor, 1971) was probably the first to note this relationship between information and trading friction, with numerous other important papers following (see e.g. Kyle, 1985; Easley and O’Hara, 1987; Admati and Pfleiderer, 1988; Glosten, 1994).

## 2.3 Liquidity Measures

Amihud, Mendelson and Pedersen (2005) point out that all liquidity measures proxy liquidity with error. This is because (i) a single measure can’t capture all aspects of liquidity; (ii) estimates derived empirically are always noisy estimates of the true parameter, and (iii) use of low-frequency data increases noise in the measurement of liquidity. Nonetheless, there are several liquidity measures that are both intuitively appealing and appear statistically promising as proxies for aggregate liquidity in the financial markets.

Trading volume is clearly related to asset liquidity: it is often used to measure the existence of numerous market participants and transactions (Sarr and Lybek, 2002). Brennan, Chordia and Subrahmanyam (1998) document a significant negative relationship between a stock's dollar trading volume and return, regardless of the method used to adjust risk-adjust the returns. This would seem to be evidence of a liquidity premium in stock returns. Turnover, the ratio of a company's outstanding stock traded within a certain time period, is another often used liquidity measure in finance literature.

Besides the supply of market participants, liquidity can be measured through transaction costs. To buy an asset at a given time, you have to pay more for it than what you would receive for selling it. This bid-ask spread is a cost resulting from trading and a common market liquidity measure. It's easy to see that if an investment strategy requires lots of trading, then the costs of implementing that strategy will increase with the bid-ask spread and this affects liquidity. Sarr and Lybek (2002) argue that bid-ask spreads may capture both the explicit and implicit costs of trading. Besides order processing costs, spreads may reflect asymmetric information costs, inventory carrying costs and costs resulting from oligopolistic market structure among market makers. These implicit costs are modeled in price impact measures of liquidity, such as Kyle's Lambda (Kyle, 1985) and the Amihud illiquidity measure (2002). These measures are based on the idea that market makers cannot distinguish between informed traders and liquidity traders (noise traders). On average, market makers lose trading with informed traders and profit trading with noise traders that are willing to pay for liquidity. Market makers profit maximization means that the price impact of trading increases with order flow.

In addition to price impacts of trading, return reversals following trades are often used in literature to proxy for market liquidity. The Pastor-Stambaugh (2003) liquidity measure is probably the most widely used return reversal liquidity measure. This measure links contemporaneous trading volume with future return reversals. Pastor and Stambaugh argue that their liquidity measure captures the market makers reward from providing liquidity. Sadka (2006) also bases the estimation of systematic liquidity on return reversals by dividing transaction price impacts into those that persist and those that are reversed. A permanent change in the price of an asset implies a change in its intrinsic value, and depends on the amount of noise trading versus informed trading. A transitory price change depends on market making costs, such as inventory risk, order processing and the risk of informed trading. Aggregating Sadka's return reversal measures into a market-wide liquidity shock estimate suggests that the permanent-variable component of return reversals is priced in stock returns.

## 2.4 Commonality and Persistence of Liquidity

Commonality in liquidity emerged as a research topic in the late 1990s – previously the focus had been on individual securities liquidity measures instead of market-wide movements in liquidity. Studies suggest that liquidity is not just a single asset attribute. In fact, individual liquidity measures co-move with each other – thus there is empirical evidence of commonality in liquidity. Sensitivity to systematic variation in liquidity should be priced. This in turn has implications for mutual fund management.

Chordia, Roll and Subrahmanyam's studies (2000, 2001), CRS hereafter, were among the first ones to investigate commonality in liquidity. CRS (2000) find that individual stocks' liquidity measures exhibit co-movement and discuss possible explanations for commonality in liquidity. These explanations focus on the determinants and role that market maker inventory levels have on liquidity and liquidity measures. Firstly, market-wide price swings generally affect trading activity. As trading volume is an important determinant of dealer inventory, its variation is likely to cause changes in optimal inventory levels which in turn lead to co-movement in liquidity measures such as bid-ask spread and market depth. Inventory carrying costs depend on market interest rates, and must therefore also co-move as interest rates fluctuate. Other possible explanations for co-movement in inventory costs and liquidity include market volatility, program trading and funds' investing styles. These are factors that induce similar trading needs and inventory pressure across broad market sectors. CRS argue that if there is commonality in liquidity, then this should constitute a source of non-diversifiable price risk. However, they do not investigate the pricing of this risk, but mainly document evidence of the commonality and co-movement in liquidity.

In their second paper about the topic, CRS (2001) further investigate the determinants and time-series properties of market-wide liquidity. They choose possible explanatory variables for liquidity that are related to (i) costs of holding market maker inventory and (ii) informational trading. Specifically, CRS find that equity market returns and volatility, short-term interest rates and the term spread influence liquidity. One of their most interesting observations is that quoted bid-ask spreads increase significantly in down markets, but do not show a correspondingly strong decline in up markets. The findings support the idea that market participants, including mutual funds, could benefit from the ability to predict and time market-wide liquidity.

Huberman and Halka (2001) point out that most of market microstructure literature focuses on the liquidity of individual securities, whereas asset pricing studies focus on the relationship between systematic risk and return. They fill in on this gap by studying the time-series properties of two liquidity proxies – spread and depth – and find evidence of a systematic component of liquidity. The results hold controlling for returns, volatility, volume, interest rates and other variables possibly correlated with co-movements in liquidity. Huberman and Halka also find that the common variation in liquidity proxies is positively correlated with returns and negatively correlated with volatility. They argue that this systematic variation in liquidity is due to the presence of noise traders, who trade on non-information as is if it were information. This is because informed traders are reluctant to trade with each other, so that without the presence of noise traders there wouldn’t be any trading (Milgrom and Stokey, 1982). They further conclude that noise traders interpret the trades and price changes caused by other noise traders and this would create a market-wide component in liquidity. However, the mechanism for this is left somewhat unclear. Huberman and Halka’s study coincides with those of Chordia, Roll and Subrahmanyam (2000) and Hasbrouck and Seppi (2001), who use different data and methods to investigate commonality in liquidity.

In later studies, Hameed, Kang and Viswanathan (2010), HKV hereafter, come to conclusions similar to Chordia, Roll and Subrahmanyam (2001), and show that liquidity decreases and commonality in liquidity increases significantly after negative asset market returns. Lagged negative returns seem to have a much larger impact on bid-ask spreads than positive returns. They theorize this is due to capital constraints of financial intermediaries tightening as asset values decline. They also find empirical evidence that liquidity commonality responds asymmetrically to positive and negative market returns. Thus improvement in aggregate liquidity is not as strong after positive market returns as is the decline in down markets. As HKV point out, there are numerous theories presented in finance literature about the asymmetrical response of market liquidity to market returns. The underlying dynamic, in most cases, is the same: large market declines increase demand for liquidity as investors liquidate their positions and decrease supply of liquidity as liquidity suppliers hit their wealth or funding constraints. Examples of theories include market makers' funding constraints (increasing margin requirements in down markets), tighter risk management by institutions in response to declining markets and increased volatility, and traders' trading limits that trigger selling so that so called liquidity black holes emerge.

Domowitz, Hansch and Wang's study (2005) is interesting as it addresses the concept of systematic liquidity from a portfolio choice and asset allocation point of view. Domowitz et al. show that liquidity commonality is due to co-movements in supply and demand, caused by correlation between different order types. Their starting assumption is that market orders (a buy or sell to be executed immediately at the current market price) always consume liquidity, whereas limit orders (a buy or sell to be executed at a specific price or better) always supply liquidity. Domowitz et al. argue that stocks that are not highly correlated in returns, i.e. would be favorable for portfolio diversification purposes, can be significantly correlated in liquidity. They also document the asymmetry in systematic liquidity with respect to market returns. Systematic liquidity would seem to be an important risk factor by itself and separable from market return movements. The conclusion is that liquidity risk should be managed separately and minimized jointly with portfolio return risk. Also the downside risk in innovations to aggregate liquidity is highlighted as in previous studies.

It seems often to be the case that liquidity squeezes accompany declining asset returns and occur during times of economic downturn. Eisfeldt (2004) argues that co-movement in market liquidity and the state of the economy is in fact demonstrated in the variation of spreads between liquid and illiquid assets over the business cycle, and that liquidity crises are associated with economic downturns. Eisfeldt's model suggests liquidity is procyclical: liquidity increases with better economic conditions. Brunnemeier and Pedersen (2009) study market liquidity from an investor funding perspective and develop a model that presents added support to the empirical findings of commonality in liquidity. Their study suggests that market liquidity co-moves across assets, because changes in funding conditions affect speculators' liquidity provision in all assets and markets. Speculators smooth price fluctuations and finance trades through collateralized borrowing from financiers who set margin requirements to control their own risk. Flights to liquidity occur because tightening funding results in investors preferring less risky assets. Funding conditions move with the market – thus liquidity also moves with the market.

Pastor and Stambaugh (2003) use their own liquidity measure to test for commonality in liquidity. They calculate the measure for NYSE listed stocks, divide into decile portfolios based on market value and conclude that the change liquidity between any of the decile portfolios is positively and statistically significantly correlated.

## 2.5 Systematic Liquidity and Asset Returns

### 2.5.1 *Stock Market*

Are stock returns sensitive to aggregate market liquidity? If market liquidity is a priced state variable, then fund managers benefit from an ability to predict future market liquidity. The positive return-illiquidity relationship was first brought up by Amihud and Mendelson (1986) who investigated the relationship between securities' bid-ask spreads and returns, and found that asset returns are increasing in the bid-ask spread. The effect of the bid-ask spread on required returns was discussed earlier in more detail. However, the role of *aggregate* liquidity in stock returns emerged later as a research topic. Amihud's (2002) study on illiquidity and stock returns is one of the most widely quoted studies on stock market pricing of illiquidity. Amihud's main finding is that stock excess returns seem to contain an illiquidity premium. He presents evidence that expected market illiquidity positively affects ex-ante stock excess returns, i.e. increases the required return on a stock. Unexpected increases in market illiquidity lower contemporaneous stock prices due to an increase in the illiquidity premium. This is because higher realized illiquidity raises expectations of future illiquidity.

Amihud developes a measure of illiquidity, which has become one of the most commonly used proxies in studies related to liquidity and stock returns. The Amihud illiquidity measure is computed as the daily ratio of absolute stock return to its dollar volume averaged over some time period. It serves as a rough measure of the price impact of trading. Amihud (2002) uses data on NYSE listed stocks during 1964-1997 and finds that illiquidity has a positive and highly significant effect on stocks' expected return. Thus the study presents strong evidence that aggregate liquidity is a priced state variable in stock returns, and that investors require a premium for holding stocks that are more sensitive to market-wide illiquidity. Additionally, Amihud reports that the illiquidity effects are strongest for small companies. This could be because unexpected increases in illiquidity cause a so called flight to liquidity (larger companies become relatively more attractive to investors).

Amihud elaborates on the excess return-illiquidity relationship, pointing out that the obvious liquidity costs such as brokerage fees and bid-ask spreads are higher for equities than they are for treasuries. Also, the cost of trading large amounts of a security is higher in the equity market than in the treasuries market, where very large amounts of securities can be traded without price impact. Clearly this is not the case for stocks, with block transactions resulting in significant price reactions. Thus the excess yield on stocks over Treasury securities should not only compensate for risk but for illiquidity as well.

Pastor and Stambaugh (2003) find that stocks with higher return sensitivity to changes in aggregate liquidity have significantly higher expected returns, even after accounting for exposures to market return, size, value and momentum factors. They develop a measure of liquidity that is often used in later liquidity related studies. Specifically, they focus on temporary price changes caused by order flow, and form a measure of aggregate liquidity. Pastor and Stambaugh's findings support the theory of market-wide liquidity as a priced state variable in stock returns. Stocks' sensitivities to innovations in liquidity (liquidity betas) seem to have a significant effect on expected returns. During 1966-1999, the return spread between high and low predicted liquidity beta stocks averages 7.5 % annually. This result is statistically significant and accounts for the Fama-French and momentum factors. Pastor and Stambaugh also point out that their measure of market-wide liquidity experiences several sharp declines during the past decades, and that these declines usually coincide with market downturns and investors' apparent flight to quality. In fact, their liquidity measure is significantly positively correlated with market returns, which suggests that a high (low) level of aggregate liquidity is associated with high (low) contemporaneous market returns. These findings imply that by being able to predict and time future market liquidity, fund managers could increase market exposure prior to higher liquidity and increasing returns, and vice versa.

Jones (2002) measures aggregate liquidity and finds that the expected annual stock market return increases with the previous year's bid-ask spread and decreases with the previous year's turnover. Jones gathers bid-ask spread and turnover data of NYSE listed stocks starting from 1900 and explicit transaction cost data starting from 1925. This enables studying time variation in aggregate liquidity and its effect on asset pricing. The results point out a clear relationship between systematic liquidity and returns, and also the persistence in aggregate liquidity. Time series variation in market liquidity seems to be an important determinant of stock returns. Acharya and Pedersen (2005) provide further evidence that asset prices are affected by liquidity risk and commonality in liquidity. They develop a model in which a security's return depends on its expected liquidity and the covariance of its own return and liquidity with the market return and liquidity. As a proxy for liquidity they use the Amihud (2002) illiquidity measure. Their findings suggest that positive shocks to illiquidity are associated with low contemporaneous returns and high predicted future returns. They also conclude that the liquidity-adjusted CAPM explains returns data better than the standard CAPM.

Acharya and Pedersen's model shows that firstly, investors require a return premium for a security that is illiquid when the market is illiquid, i.e. has a high "illiquidity-beta". This effect however seems to be relatively small. Second, they estimate that investors prefer securities with high returns when the market as a whole is illiquid. A flight to liquidity often occurs in down markets, and thus illiquid securities are those that have the highest liquidity risk. This result is in line with the findings in Pastor and Stambaugh's (2003) study suggesting that sensitivity to market liquidity is priced. Third, Acharya and Pedersen find that the covariance of a security's illiquidity with market returns seems to be the most important source of liquidity risk, thereby causing the highest return premium. Based on this, Acharya and Pedersen conclude that investors are willing to pay a premium (i.e. require lower returns) for a security that is liquid when market returns are low. Finally, Acharya and Pedersen's model shows that due to persistence in liquidity, aggregate liquidity predicts future returns and co-moves with contemporaneous returns. In other words, a negative shock to liquidity predicts low future liquidity; this in turn raises required returns and lowers contemporaneous prices.

### *2.5.2 Bond Market*

Lin, Wang and Wu (2011) extend the work of Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) to the corporate bond market. They find that liquidity risk is an important determinant of expected bond returns. Specifically, Lin et al. include market-wide liquidity as a state variable in the corporate bond pricing model to investigate whether liquidity risk is priced in bond returns. They study the cross section of corporate bonds during 1994-2009 and use the Amihud (2002) illiquidity measure and the Pastor and Stambaugh (2003) and Sadka (2006) liquidity measures. The results strongly suggest that these same equity-based liquidity factors that price systematic liquidity risk in the cross section of equities also price bond returns. This relationship is positive and statistically significant even after controlling for other risk factors and bond characteristics. The average return on bonds with high sensitivities to aggregate liquidity innovations exceeds that of bonds with low sensitivity by approximately 4% annually. There is a significant positive relation between liquidity beta and expected bond returns.

De Jong and Driessen (2006) study the effect of systematic equity and bond market liquidity measures on the pricing of corporate bonds in the US and in Europe. They show that corporate bonds have significant exposure to innovations in both Treasury bond liquidity and equity market liquidity. Monthly changes in the bid-ask spread of long-term US Treasury bonds proxy for fixed income market liquidity and the Amihud illiquidity factor for systematic liquidity in equities. Empirical evidence suggests that corporate bonds are exposed to systematic liquidity shocks in both markets: the estimated liquidity premium in expected bond returns is approximately 0.6% for investment grade bonds and 1.5% for speculative grade bonds. Acharya, Amihud and Bharath (2009) continue expanding the study of de Jong and Driessen by using a longer time series and by isolating the so called regime-switching behavior of liquidity betas. In addition to confirming the results of de Jong and Driessen, they find that while investment grade bond returns fall when stock- or treasury markets become illiquid, the returns of speculative grade bonds rise substantially. In other words, the prices of junk bonds fall as market liquidity decreases. This observation of a flight to quality holds after controlling for other systematic risks.

## 2.6 Commonality Between Stock and Bond Market Liquidity

Research on systematic liquidity has mostly focused on stock and bond markets separately. Chordia, Sarkar and Subrahmanyam (2005) explore cross-market dynamics in liquidity and find that innovations to stock and bond market liquidity and volatility are significantly correlated. There seem to be common factors that drive liquidity in both markets. The unconditional correlation in stock and bond market returns is low, but volatility in these markets seems to be correlated. This could cause commonality in liquidity, for example by affecting the inventory risk of market makers (Ho and Stoll, 1983). CSS point out that trading activity can also create commonality between markets, as many trading strategies are implemented by shifting allocations between stock and bond markets. Furthermore, there are factors that might make order flows in these two markets complementary. As an example CSS mention an expansion in monetary policy, which could increase order inflows in both stock and bond markets and affect their liquidity. Other market-wide wealth and information shocks could also induce commonality in liquidity across markets.

CSS use bid-ask spread and depth, returns, volatility and order flow data during 1991-1998 in the equity and fixed income markets to investigate liquidity dynamics between these two markets. They find that innovations to liquidity and volatility are significantly correlated in the stock and bond markets. Also, volatility shocks are informative in predicting shifts in liquidity in both markets. As an example, the results of CSS show that innovations to stock volatility forecast an increase in bond spreads. CSS also find evidence that liquidity in both markets is lower during down markets, which could also be due to constraints in market making.

Goyenko and Ukhov (2009) build on the study of Chordia, Sarkar and Subrahmanyam (2005). They find a lead-lag relationship between stock and bond market illiquidity: positive shocks to stock illiquidity decrease bond market illiquidity, which is consistent with flight-to-quality and flight-to-liquidity episodes. A positive shock to bond illiquidity, on the other hand, increases stock illiquidity as well.

## 2.7 Liquidity Risk and Mutual Fund Returns

The role of liquidity risk in fund returns has recently emerged as a popular topic in finance literature. A very recent study by Dong, Feng and Sadka (2011), DFS hereafter, is closely related to Cao, Simin and Wang's (2010) study on mutual funds' liquidity timing. DFS pose an interesting question: are mutual funds that hedge against systematic liquidity (funds that have a low liquidity beta) relatively more expensive (have lower returns)? Their study presents evidence that fund performance is significantly linked to the level of the fund's exposure to liquidity risk.

DFS calculate the liquidity risk of a mutual fund as the covariation of fund returns with unexpected changes in aggregate liquidity (liquidity beta). They use the Sadka (2006), Amihud (2002) and Pastor and Stambaugh (2003) liquidity measures to proxy for aggregate liquidity and find that, on average, funds that significantly load on liquidity risk subsequently outperform funds with lower exposure to market liquidity. Over the period 1983-2009 this return spread is on average 6% annually. This result holds after controlling for Fama-French (1996) factors, momentum (Carhart, 1997) and fixed income related factors. During times of significant market liquidity squeezes, however, funds loading on liquidity risk underperform. DFS also conclude that the liquidity risk return spread between liquidity hedgers and liquidity loaders does not depend on fund investment style. Dong, Feng and Sadka present strong evidence that liquidity risk exposure affects mutual fund returns. This suggests that the same liquidity factors that affect pricing of stocks, bonds and hedge funds also affect mutual fund returns. This sets an interesting starting point for a study on mutual funds' liquidity timing ability.

DFS link their study to several previously documented observations about mutual fund performance. They show that momentum in mutual funds' returns (e.g. Carhart, 1997) might be due to greater liquidity exposure in the outperforming funds. They also apply their liquidity exposure theory to the previously documented smart-money effect, which means that funds experiencing investor inflow subsequently outperform funds that experience investor outflow. DFS find that the smart-money effect is mostly present among funds that have high exposure to liquidity risk.

Unlike hedge funds, which may have lock up periods, mutual funds are required by law to allow shareholder redemptions at any time. Edelen (1999) notes that mutual funds engage in a substantial amount of uninformed, liquidity motivated trading. He suggests that this liquidity service provided to satisfy individual investors' liquidity trading needs could be the cause for the well-documented underperformance of mutual funds, and also the lack of (or negative) timing ability observed in some studies. Rinne and Suominen (2010) estimate mutual funds' costs of immediacy, and find evidence that mutual funds incur significant costs due to their liquidity needs. They argue that the costs of demanding liquidity vary substantially between different types of funds, but on average funds appear to have annually lost 0.7% of assets under management due to trading costs arising from requiring immediacy. Da, Gao and Jagannathan (2011) claim that some funds are capable of acting as liquidity providers and make returns, whereas others suffer the costs of demanding immediacy. Several studies investigate whether fund-level liquidity affects future fund performance, but little evidence of a dependency is found. This is discussed next.

## 2.8 Mutual Funds' Liquidity Management and Preferences

The role of liquidity in investment management has emerged as a research topic in the 2000s. Events such as the collapse of the hedge fund Long Term Capital Management in 1998[1] highlight the importance of liquidity risk in portfolio management. As Massa and Phalippou (2005) point out, mutual funds demand liquidity for two important reasons. The first is to prepare to meet future redemptions by shareholders. The second motive is more speculative, and is related to the cost of fund strategy implementation. That is, if strategy implementation involves lots of trading and portfolio rotation, then the liquidity of assets held gains importance. Yet portfolio liquidity hasn't been treated as a choice variable in very many studies so far.

The observation that liquid stocks seem to command lower returns (discussed in Section 2.5) and the striking commonality in aggregate liquidity (discussed in Section 2.4) highlight the importance of liquidity management and suggest that there is a so called optimal level of portfolio liquidity. Lo, Petrov and Wierzbicki (2003) are among the first to study liquidity in a portfolio optimization context. They incorporate liquidity factors in the traditional mean-variance portfolio optimization framework and find that liquidity optimized portfolios have some very attractive properties. Even simple forms of liquidity optimization at the portfolio level seem to yield significant benefits by reducing liquidity risk exposure without significantly sacrificing expected return per unit risk.

Lo et al. define three ways to incorporate liquidity management into the investment process: selecting individual investments based on their liquidity, setting a minimum level of portfolio liquidity, and direct optimization of a mean-variance-liquidity efficient portfolio. They argue that simple optimization procedures can yield mean-variance efficient portfolios that are significantly more liquid than non-liquidity-optimized portfolios. Whether mutual funds actually engage in any kind of liquidity optimization is left unanswered. In their study Lo et al. use simple liquidity measures such as trading volume, turnover and the percentage bid-ask

[1] LTCM, the US hedge fund, was extremely levered and also significantly exposed to liquidity risk by design: it went short liquid instruments and long less liquid instruments. These positions were established across a variety of countries and markets. When the Russian debt crisis triggered a sharp decline in market liquidity, the LTCM portfolio experienced large losses and a need for liquidations to meet margin calls. This further eroded LTCM's position. Prior to the liquidity squeeze, the hedge fund's liquidity sensitive strategies had paid off in returns. (Pastor and Stambaugh, 2003)

spread, construct these for individual securities by using daily data and then use these to measure portfolio level liquidity.

Massa and Phalippou (2005) are the first to investigate the relationship between mutual fund liquidity and other fund characteristics. They study actively managed US equity funds during 1983 to 2001 to test whether differences in funds' liquidity needs predict their performance. Massa and Phalippou present several interesting insights into the liquidity management of mutual funds, and find evidence that funds engage in active liquidity management. One would expect that in order to "buy liquidity", mutual funds sacrifice some return. However, if the mutual fund market was competitive and liquidity costly, liquid funds would underperform and eventually disappear (Berk and Green, 2004). Massa and Phalippou find that net fund performance isn't related to fund liquidity unconditionally and conclude that the fund industry is competitive. In other words, fund liquidity on average does not affect performance.

However, Massa and Phalipppou's most interesting discovery is that shocks to market-wide liquidity affect fund performance. Specifically, *liquid* funds strongly overperform during *illiquid times* and underperform during liquid times. Unpredictable changes in market liquidity seem to affect fund performance. Liquidity conditionally affects fund performance, and this effect seems to be significant both economically and statistically. The top quintile of liquid funds outperforms the bottom quintile (illiquid funds) by approximately 1.4 % monthly during the most illiquid months. During liquid months the opposite holds: the liquid funds underperform by approximately 0.8%. Short-term divergences from a fund's so called optimal liquidity level also seem to affect fund performance. Funds that deviate most from the so called optimal liquidity level underperform those that deviate least. Yet, funds that invest in liquid stocks do not significantly differ in performance from those that invest in illiquid stocks.

Massa and Phalippou present evidence that equity mutual funds adjust the level of fund liquidity based on portfolio liquidity needs. They divide liquidity needs into two categories: those preparing for meeting future redemptions, and those related to investment strategy implementation. Fund size seems especially important in determining the level of chosen liquidity. Trading frequency, degree of portfolio concentration and cash holdings are also found to be important determinants. No predictability in fund performance with respect to portfolio liquidity is found. Massa and Phalippou also conclude that funds' liquidity needs may in fact reinforce a valuation spread between liquid and illiquid stocks. This is consistent with Acharya and Pedersen’s (2005) findings that liquid stocks tend to have superior performance in illiquid times.

Additionally, Massa and Phalippou analyze the dynamic relationship between portfolio liquidity, liquidity needs and liquidity shocks, and find evidence of active liquidity management in mutual funds. In other words, their study suggests that funds alter the level of portfolio liquidity consistently with changes in both liquidity needs and shocks to market-wide liquidity. For example, portfolio liquidity is strongly and consistently related to portfolio size. Furthermore, evidence suggests that portfolio managers appear to rebalance their portfolio to offset changes in liquidity conditions. This gives support to the theory that investors include liquidity into their portfolio decisions, and that the liquidity of an asset affects required returns. Finally, Massa and Phalippou argue that both changes in funds’ liquidity level and shocks to market-wide liquidity are uncorrelated and unpredictable over time, so that investors cannot take advantage of this information.

Studies on mutual funds’ liquidity management provide an interesting background and motivation for a study on whether mutual funds actually show ability time market liquidity. The concluding section of the literature review shortly discusses the relation between liquidity and market efficiency.

## 2.9 Liquidity and Market Efficiency

Since market illiquidity by definition reduces trading in financial assets, variations in the level of liquidity could affect market efficiency. Chordia, Roll and Subrahmanyam (2008) continue their studies on liquidity by addressing this question. There are alternative ways to define market efficiency. Traditionally, the idea of efficient markets emphasizes the lack of return predictability: asset prices should follow a random walk (Fama, 1970). The market microstructure literature uses a different approach: to what extent is private information reflected in asset prices. If markets become more liquid, for example due to a reduction in tick size and a resulting decrease in bid-ask spreads, then the decrease in trading costs could increase trading on private information and incorporate it into prices. CRS also point out that short-horizon return predictability should be diminished by arbitrage trading, which should be more active during times when the market is more liquid. As both academic studies and recent market events have shown, market liquidity can vary greatly over time and sometimes decreases significantly or even disappears.

CRS use return, order flow and liquidity data on NYSE stocks during 1993-2002 to study the relationship between market liquidity and efficiency. They present two competing hypotheses about the way that liquidity, order flows and return predictability can be related. Firstly, if market makers are limited in their risk bearing capacity, prices can deviate from fundamental values. Traders who are able to detect such deviations may submit arbitrage trades, which would make prices converge to fundamental value. However, market illiquidity may increase trading costs to such extent that arbitrage trading does not happen. This creates a link between market liquidity and efficiency. Alternatively, market makers might be unable to detect information content in order flow and fail to eliminate return predictability. Outside agents would then have an incentive to gather information on order flow and trade on it. To the market maker this presents an adverse selection problem and might reduce market liquidity. In this way, market efficiency could actually be associated with less liquidity.

CRS present empirical evidence that intraday market efficiency is closely linked to daily market liquidity. Return forecastability from order flows is significantly reduced on more liquid trading days. Another important finding is that market efficiency has significantly improved with the reduction of the minimum tick size (a decrease in bid-ask spreads). Also, price movements seem to be closer to a random walk in more liquid trading conditions. Return autocorrelations decrease with the tick size, and this evidence points to an increase in informational trading. As would seem intuitive, liquid market conditions stimulate arbitrage activity and thereby improve market efficiency. Chung and Hrazdil (2010) report similar results and conclude that increased liquidity attracts arbitrage trading, which helps market makers absorb investor demand and makes markets more efficient. In a later paper, CRS (2010) investigate the trends in trading activity and market quality, and find that during their sample period 1993-2008 trading activity has increased sharply, and this has been accompanied by a sharp increase in more frequent smaller trades and more informational trading by institutions. They also estimate that prices conform more closely to a random walk in recent years, which would be due to increased trading and declining costs of trading, in other words improved liquidity.

# 3 Hypotheses

This thesis examines whether US mutual funds are able to time aggregate stock market liquidity. That is, my main goal is to investigate whether fund managers increase (reduce) market exposure in anticipation of more liquid (illiquid) market conditions. In the thesis I test whether the use of alternative liquidity measures gives further support to Cao, Simin and Wang's (2010) findings of positive liquidity timing ability among mutual funds. Cao, Chen, Liang and Lo (2011) report even stronger timing ability for hedge funds. Thus the main hypothesis is as follows:

*H1: US mutual funds exhibit ability to time market liquidity, so that they increase (decrease) market exposure prior to increases (declines) in aggregate liquidity.*

So far the evidence of timing ability is mixed: in contrast to Cao et al., Winter (2011) uses alternative methodology and reports negligible or negative timing skill. In addition to the average timing ability of mutual funds, I examine cross-sectional differences in timing success between different types of funds. Cao, Simin and Wang (2010) find that funds with riskier investment strategies show significantly stronger liquidity timing ability than the less risky funds. This formulates my second hypothesis:

*H2: The level of riskiness of a fund's investment strategy affects the fund's ability to time market liquidity.*

This hypothesis is intuitively appealing, as it sounds plausible that riskier funds have more flexibility in implementing investment strategies in response to changes in the market environment. In addition to investment strategy, there are other fund characteristics that might be related to a fund's liquidity timing performance. As it is reasonable to assume that liquidity timing is a valuable service to investors, both as a hedge and in the form of higher returns, there are certain fund characteristics that might be more pronounced among successful liquidity timers. Fund age, flows, turnover rate and expense ratio are among fund characteristics that may be positively related to timing ability – funds that perform better should last longer, attract investors, possibly trade more actively to implement management's views, and be able to charge higher fees. Thus my third hypothesis is as follows:

*H3: Fund timing ability is positively related to certain fund characteristics. Specifically, fund age, average fund flows, fund turnover rate and expense ratio could be positively related to liquidity timing.*

There are also certain fund attributes that may have a negative relationship with a fund's liquidity timing success. As funds are often forced to either liquidate or increase holdings in response to investor redemptions and subscriptions, it may be difficult for fund management to control market exposure and implement strategies of liquidity timing. The volatility of fund flows is therefore a characteristic that may be negatively related to timing ability. Another fund characteristic with possible negative relation to liquidity timing is fund size, often measured as total net assets. Large funds' trading may itself affect market liquidity: executing large trades may be costly due liquidity related transaction costs. As a result, larger funds may find it more difficult to actively implement investment strategies without incurring relatively large costs. The fourth hypothesis is as follows:

*H4: Fund timing ability is negatively related to certain fund characteristics. Specifically, fund flow volatility and fund size could be negatively related to liquidity timing.*

In addition to testing for the aforementioned relationships, I run several robustness checks on my data to check for possible biases. The next section discusses the data and methods used.

# 4 Data and Methods

## 4.1 Fund Data

I choose to use data from the United States, as this market provides by far the most extensive data set suitable for the study. Data for mutual funds come from the CRSP Survivor-Bias-Free US Mutual Fund Database. Due to limitations of the database organization and reporting, identifying mutual funds' main asset classes is very difficult; therefore I include all funds in my sample and adjust for different asset classes later in the tests that I perform. The fund data are monthly and range from January 1980 to December 2010.

For each year I include in the sample funds that have monthly returns reported for each month of that year. Index funds are removed from the sample, as their goal is to replicate the performance of a benchmark index and they are therefore unlikely to display market timing of any kind. When available, I use the Index Fund Flag provided by the database to identify and separate index funds from the sample. Otherwise I identify index funds by their names.

Mutual fund families introduced different share classes in the 1990s. When a fund has two or more share classes, only one of those is included in the sample. This is because holding compositions of different share classes are usually the same. The resulting data set consists of altogether 1,745,064 monthly fund return observations.

A summary of descriptive statistics for funds is presented in *Table 1*. Funds are grouped into three categories based on their Wiesenberger, Lipper and Strategic Insight objective codes[2]. These categories are aggressive growth, growth and growth and income funds[3]. Funds that cannot be classified are included in the "All funds" category. Fund classes serve as a rough estimate of the riskiness of the fund's investment strategy. Fund class information is available in the CRSP Survivor-Bias-Free Mutual Fund Database for 4,325 funds during the sample period 1980-2010.

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[2] Aggressive growth funds are those whose Wiesenberger codes are SCG, AGG and MCG, whose Strategic Insight codes are AGG and SCG, or whose Lipper codes are CA, LSE, MR and SG. Growth funds include those with Wiesenberger codes of G, G-S, S-G, GRO, and LTG, Strategic Insight codes of G, GRO, and GMC, or Lipper code of G. Growth and income funds are those with Wiesenberger codes of GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G and GRI, Strategic Insight code of GRI, or Lipper codes of GI and MC.

[3] A fourth category, income funds, is also available but omitted in my study. This is because income funds mainly invest in fixed income and this distorts results and complicates comparison with the other fund classes.

The final sample contains altogether 21,500 actively managed mutual funds, of which 937 are aggressive growth funds, 883 growth funds and 2,113 growth and income funds. The average monthly return is highest for growth funds (0.83%) and lowest for aggressive funds (0.63%). The average monthly return for all funds during 1980-2010 is approximately 0.60%. Monthly return standard deviation is also highest for growth funds (5.14%) and lowest for growth and income funds (4.43%). The average monthly return volatility for the entire fund portfolio is 4.39%, or approximately 15.2% on an annual level. The highest monthly return observation for mutual funds is approximately 170% and the lowest -90%, which highlights the dispersion in fund performance data.

**Table 1**
**Summary of Fund Characteristics**

Descriptive statistics of mutual fund characteristics from January 1980 to December 2010. Statistics are reported for aggressive growth, growth, growth and income and all funds respectively. Average monthly returns (in percentages) and monthly return standard deviations (in percentages) are calculated for equally weighted portfolios of mutual funds within each fund category. Size is calculated as average fund TNA averaged across funds in each category. Age is defined as the number of years between the last return date in the database and the first date the fund was offered, and then averaged across funds within each fund category. Standardized monthly flows, expense ratios and turnover rates are also averaged over time for each fund, and then averaged across funds within each fund category. The last row, non-survivors, reports the percentage of defunct funds in each category.

| | Aggressive Growth | Growth | Growth & Income | All funds |
|---|---|---|---|---|
| Number of funds | 937 | 883 | 2 113 | 21 500 |
| Return (%) | 0.632 | 0.830 | 0.674 | 0.598 |
| Return Std.Dev. (%) | 4.509 | 5.136 | 4.434 | 4.388 |
| Size ($ millions) | 225.7 | 611.7 | 381.0 | 433.8 |
| Age (years) | 10.64 | 13.53 | 12.56 | 11.29 |
| Monthly Flow (%) | -3.910 | -1.579 | -3.511 | -2.655 |
| Expense ratio (%) | 1.400 | 1.135 | 1.168 | 1.226 |
| Turnover ratio | 1.042 | 0.815 | 0.538 | 0.835 |
| Non-survivors (%) | 63.71 | 40.66 | 54.85 | 46.46 |

Growth funds are the largest in size, with average total net assets of approximately $612 million. Aggressive growth funds have the lowest average TNA of $226 million. The average size of all funds is approximately $434 million. Fund age is calculated as the number of years between the last and first return dates in the database and averaged across funds within each category. Growth funds have the longest return histories, with an average fund age of 13.5 years. Aggressive growth funds’ seem to have the shortest life spans, with an average age of approximately 10.6 years. For the entire fund sample, average fund age is approximately 11.3 years.

Monthly fund flows are calculated as the relative change in fund TNA after adjusting for the fund's return. Average monthly standardized flows are slightly negative for all fund portfolios; the aggregate fund portfolio has average monthly flows of approximately -2.65%. Aggressive growth funds experience the most negative flows (-3.91%).

Expense ratio data is scarce in the CRSP Mutual Fund Database, but the available data suggests that aggressive growth funds have the highest annual expense ratios of approximately 1.40% on average. They also have the highest turnover ratio of 1.04 annually, whereas growth and income funds seem to trade significantly less actively and have a turnover ratio of 0.54. Growth funds have the lowest average expense ratio 1.14%. The entire fund sample's expense ratio averages 1.23% annually and the turnover rate is approximately 0.84.

The aggressive growth fund category contains the highest ratio of funds that have been discontinued and merged into other funds at 63.7%, whereas only 40.7% of growth funds have discontinuing return histories. The average ratio of non-surviving funds to currently operating funds is 46.5%.

## 4.2 Liquidity Measures

This study employs three measures of aggregate market liquidity. Selection of liquidity measures is motivated by both previous studies and data availability issues. Two of the market liquidity measures, trading volume and market turnover, are related to trading activity. Thus liquidity is measured from the viewpoint of the supply of market participants and transactions. The third one, the Sadka (2006) permanent-variable liquidity measure, is related to theories of private information and market making as it is based on return reversals resulting from trading.

For measuring trading activity related liquidity, stock market data are obtained from CRSP. Data consist of stocks listed in the NYSE, AMEX and NASDAQ exchanges, and satisfy the following: 1) security is an ordinary common stock, 2) company is incorporated in the US, 3) security is not a REIT or a closed-end fund and 4) the company's SIC code is available. Data for the Sadka liquidity shock measure comes from WRDS.

### 4.2.1 Trading Volume

Trading volume is used as a liquidity proxy to measure equity market trading activity. I use NYSE, AMEX and NASDAQ data from CRSP to calculate monthly estimates of dollar trading volume for each stock. I then average this data across stocks for a monthly aggregate liquidity measure denoted VOL. The liquidity timing model employs the natural logarithm of this measure, denoted as LVOL. Specifically,

$$VOL_t = \frac{1}{N}\sum_{i=1}^{N} P_{i,t} V_{i,t}, \tag{1}$$

where $P_{i,t}$ is the closing share price for company $i$ in month $t$, $V_{i,t}$ is the number of shares of company $i$ traded in month $t$ and $N$ is the number of companies included in the sample in month $t$. Thus $VOL_t$ is the estimate of average dollar trading volume per stock during month $t$.

LVOL, the liquidity measure employed in timing tests, is then simply defined as

$$LVOL_t = Log(VOL_t). \tag{2}$$

*Figure 1* displays the development of aggregate dollar trading volume in the three stock exchanges NYSE, AMEX and NASDAQ from January 1980 to December 2010. Trading volume seems to have started an increasing trend in the late 1990s, peaking during the dot com boom around 2000 and then steadily rising again until the escalation of the financial crisis starting in 2008. In the late 2000s, volatility in equity market trading volume seems to have increased dramatically.

To test for mutual funds' liquidity timing ability, I use innovations in the monthly trading volume measure rather than levels data. Innovations are calculated over the 12-month moving average of average monthly trading volume.

**Figure 1**
**Average Monthly Trading Volume**
**January 1980 - December 2010**

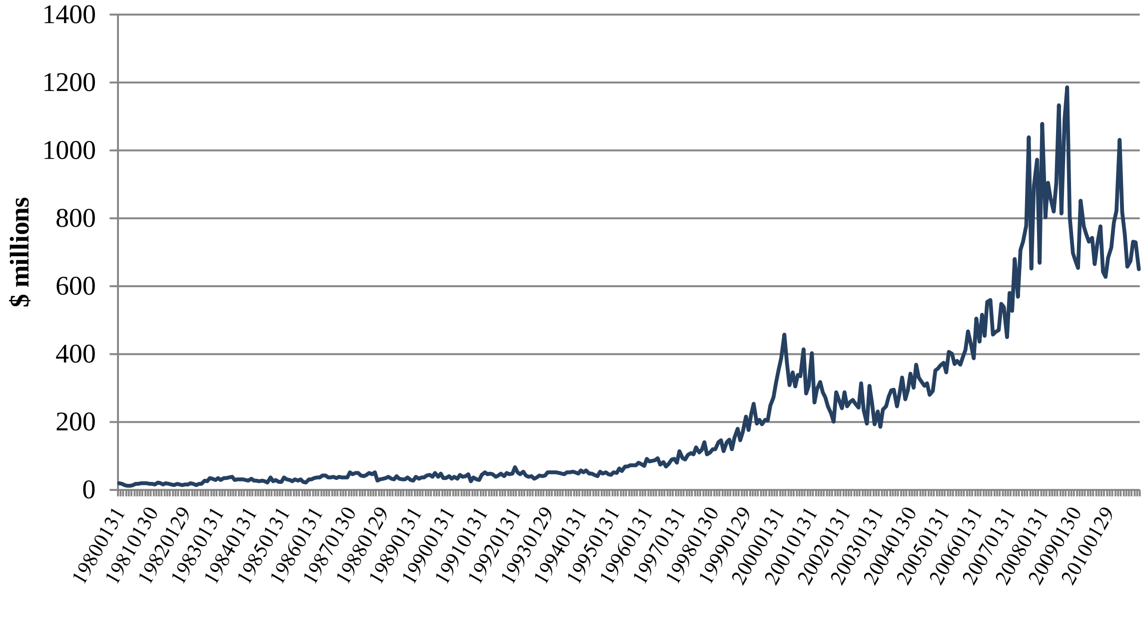


**Figure 1** Development of average monthly trading volume per stock in the NYSE, AMEX and NASDAQ exchanges during January 1980 - December 2010.

### *4.2.2 Turnover*

Turnover is the second proxy for trading activity and defined as the number of shares traded per number of shares outstanding, averaged across all stocks traded during a month. I use NYSE, AMEX and NASDAQ data from CRSP and denote turnover as TO. Specifically,

$$TO = \frac{1}{N}\sum_{i=1}^{N} Vi,t \ / S_{i,t} \ , \tag{3}$$

where $V_{i,t}$ is the number of shares of company *i* traded during month *t*, $S_{i,t}$ is the number of shares of company *i* outstanding in month *t* and *N* is the number of companies included in the sample in month *t*.

The development of average monthly share turnover per stock in the three exchanges is displayed in *Figure 2*. Like trading volume, turnover shows an increasing trend especially after the mid-1990s. The measure experiences occasional spikes but hikes significantly in 2007. As with trading volume, volatility of the turnover liquidity measure has increased considerably during and after the financial crisis that started in 2008.

For purposes of the liquidity timing tests, I use innovations in the monthly turnover measure rather than levels data. Innovations are calculated over the 12-month moving average of average monthly stock turnover.

**Figure 2**
**Average Monthly Turnover**
**January 1980 - December 2010**

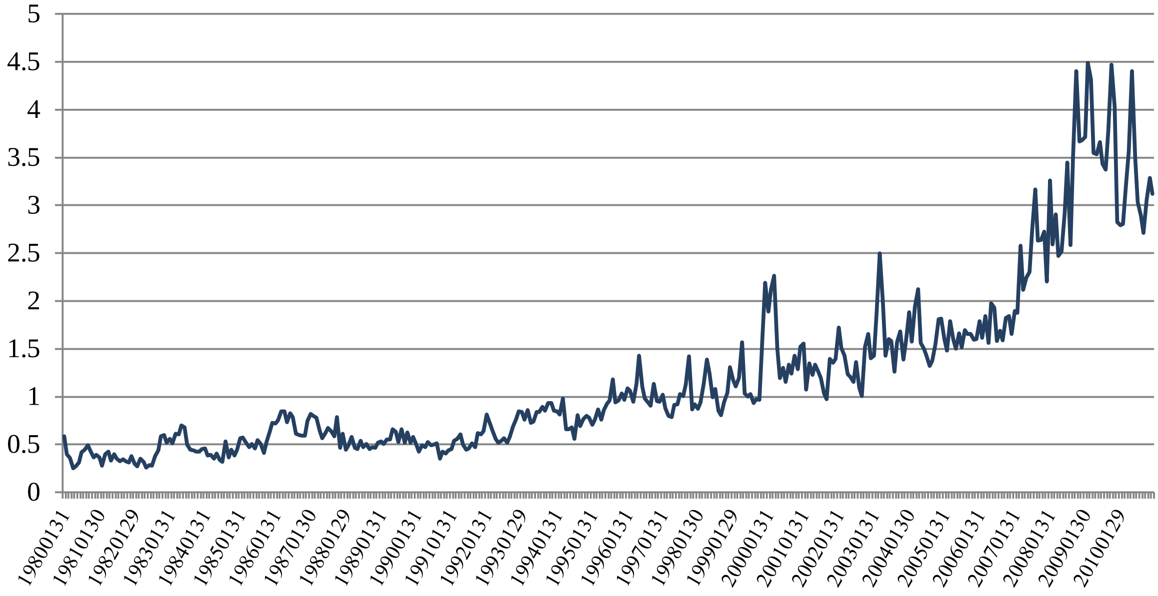


**Figure 2** Development of average stock turnover in the NYSE, AMEX and NASDAQ exchanges during January 1980 **-** December 2010.

### *4.2.3 Sadka Liquidity Shock Measure*

The Sadka liquidity measure is linked to early theories of interaction between informed traders, liquidity traders and market makers (see e.g. Kyle, 1985; Admati and Pfleiderer, 1988). The underlying idea is that trading causes price impacts – those that persist imply a change in the implicit value of the asset, whereas price changes caused by liquidity trading are reversed. Sadka (2006) uses intra-day trading data to estimate permanent and transitory price effects of trading. These firm-level liquidity risk factors are combined into a market-wide measure of liquidity shock. Sadka presents evidence that the permanent-variable component of liquidity risk explains stock returns. Furthermore, Dong, Feng and Sadka (2011) show that these innovations in liquidity are an important determinant in the cross-section of mutual fund returns. Data for the Sadka liquidity shock measure are available in the CRSP database for the years 1983-2008.

Details about the construction of the Sadka liquidity measure and the permanent-variable component can be found in Sadka's study about the role of liquidity risk in momentum and post-earnings-announcement drift anomalies (2006).

*Figure 3* displays the development of the Sadka permanent-variable liquidity shock from April 1983 to December 2008. Contradictory to the two trading volume liquidity measures, it's hard to detect any meaningful pattern of development in the Sadka measure. Unfortunately data availability ends in 2008, which leaves part of the financial crisis out of the analysis. The Sadka measure does show a substantial negative liquidity shock in September 2008, which is often considered a starting point for the escalation of the financial crisis and the resulting liquidity squeeze in the financial markets.

**Figure 3**
**Sadka Permanent-Variable Liquidity Measure**
**April 1983 - December 2008**

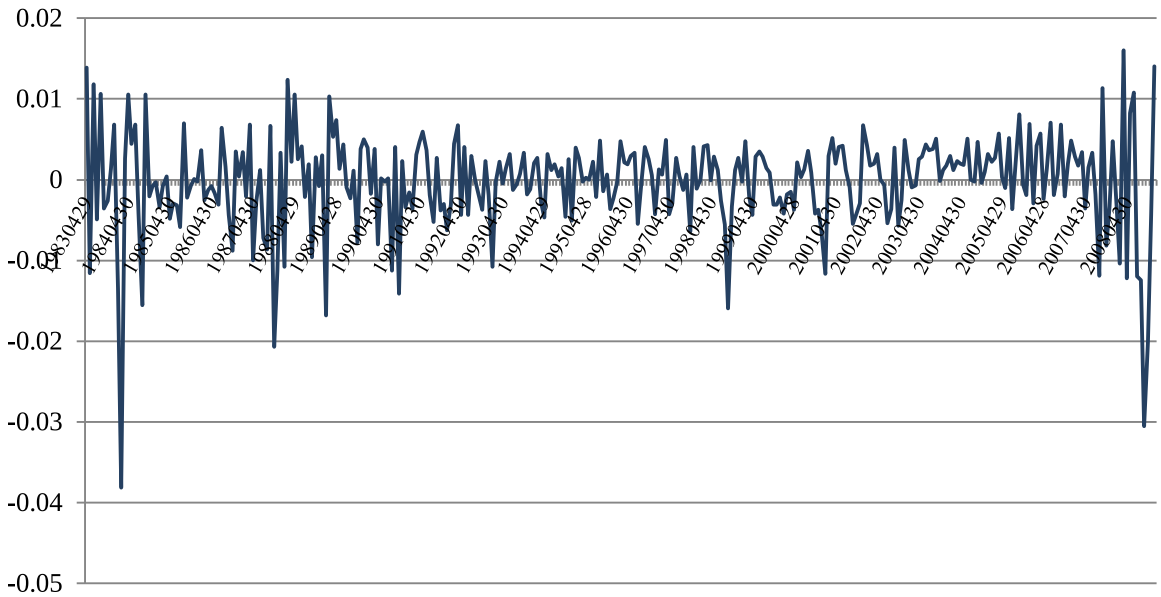


**Figure 3** Development of the Sadka Permanent-Variable liqudity measure during April 1983 **-** December 2008. The Sadka measure estimates shocks to market-wide liquidity and is calculated from intra-day trading data.

## 4.3 Other Market Data

Market returns come from CRSP and are calculated as the value-weighted total return on all NYSE, AMEX and NASDAQ stocks. Excess returns are calculated over the one-month Treasury Bill Rate.

Fama-French factors measure the returns from value and size strategies. Monthly data for the Fama-French factors SMB (historic excess returns of small cap stocks over large caps) and HML (historic excess returns of high book-to-market stocks over low book-to-market stocks) are obtained from Wharton Research Data Services (WRDS) and range from January 1980 to December 2010. The monthly Carhart (1996) momentum factor UMD is also obtained from WRDS. UMD measures the excess return of high prior return portfolios over low prior return portfolios. Additionally, I use the Barclays US Aggregate Bond Index to control for fixed income and the Barclays High-Yield Corporate Index for credit risk exposure in the sample of fund returns[4]. Data for these are obtained from Datastream.

Of the three fund classes utilized in the study, aggressive funds and growth and income funds have an equity market correlation (calculated with the S&P 500 Index) of approximately 0.6, whereas growth funds have a correlation of about 0.8. Nevertheless, adding the two factors for fixed income and credit improve the $R^2$-fit of model used for timing tests. Since it is not possible to distinguish between funds' asset classes in the sample, these two factors also gain significance.

[4] For a discussion of common factors in mutual fund returns see e.g. Sharpe (1992) or Khandani and Lo (2009).

## 4.4 Summary Statistics of Data

*Table 2* presents summary statistics for market factors used in the liquidity timing tests. The average monthly market return during 1980-2010 is approximately 0.57%. The corresponding figure for the entire fund sample is approximately 0.60%, as reported in *Table 1*. On a monthly level, market volatility has averaged 4.6% which corresponds to an annual standard deviation of about 16.3%. The highest and lowest monthly return observations for the aggregate equity market are 12% and -23%, respectively. Of the size, value and momentum strategies, momentum has produced the highest monthly returns during 1980-2010, reaching approximately 0.65% per month on average. Return standard deviation is also highest for the momentum strategy. Average monthly returns for the Barclays bond and high-yield indices, denoted by FI and CR, are 0.07% and 0.15% respectively.

**Table 2**
**Summary Statistics of Market Factors**

Descriptive statistics for market factors ranging from January 1980 to December 2010. $R_m$ denotes the monthly excess return on the CRSP value-weighted market portfolio consisting of NYSE, AMEX and NASDAQ stocks. SMB, HML and UMD denote monthly returns on factor-mimicking portfolios for size, book-to-market equity and one-year momentum in stock returns, respectively. FI denotes the monthly return on the Barclays US Aggregate Bond Index and CR the return on Barclays US High-Yield Corporate Index. All return figures are percentages.

| | $R_m$ | SMB | HML | UMD | FI | CR |
|---|---|---|---|---|---|---|
| Mean | 0.568 | 0.165 | 0.351 | 0.645 | 0.071 | 0.148 |
| St. Dev. | 4.633 | 3.169 | 3.169 | 4.784 | 1.710 | 2.676 |
| Median | 1.032 | 0.010 | 0.325 | 0.880 | 0.137 | 0.229 |
| Max | 12.43 | 22.19 | 13.84 | 18.39 | 11.37 | 13.18 |
| Min | -23.14 | -16.67 | -12.78 | -34.75 | -6.742 | -16.94 |
| Kurtosis | 2.424 | 8.336 | 2.311 | 10.799 | 6.789 | 7.973 |
| Skewness | -0.802 | 0.731 | 0.002 | -1.473 | 0.816 | -0.498 |
| Nr of obs. | 372 | 372 | 372 | 372 | 372 | 372 |

*Table 3* presents summary statistics for liquidity measures during the sample period 1980-2010. For the Sadka liquidity measure data is only available from April 1983 to December 2008.

**Table 3**
**Summary Statistics of Market Liquidity Measures**

Descriptive statistics for market liquidity measures used in liquidity timing tests. Statistics are calculated from monthly observations ranging from January 1980 to December 2010. Data for the Sadka (2006) permanent-variable liquidity measure ranges from April 1983 to December 2008. Market trading volume and turnover are calculated as the equally weighted averages of the monthly trading volumes and turnovers of common stocks traded on NYSE, AMEX and NASDAQ. Volume is expressed in dollar millions. PS VWF denotes the Pastor-Stambaugh (2003) value-weighted liquidity factor and measures the return difference between high and low liquidity portfolios.

| | Sadka PV | Volume | Turnover | PS VWF |
|---|---|---|---|---|
| Mean | 0.000 | 214.3 | 1.189 | 0.649 |
| St. Dev. | 0.006 | 259.7 | 0.905 | 3.726 |
| Median | 0.001 | 68.72 | 0.870 | 0.487 |
| Max | 0.016 | 1 187 | 4.492 | 20.90 |
| Min | -0.038 | 11.17 | 0.249 | -9.997 |
| Kurtosis | 7.188 | 1.676 | 2.232 | 2.278 |
| Skewness | -1.586 | 1.559 | 1.614 | 0.372 |
| Nr of obs. | 309 | 372 | 372 | 372 |

The Sadka permanent-variable liquidity measure averages at zero with a standard deviation of 0.006. Average monthly stock market turnover has been approximately 119%, although until the mid-1990s this figure has stayed below 100%. Average dollar trading volume per stock is approximately $214 million on a monthly level, measured across the entire sample period. During the period from 2000 to 2010 this figure has risen to approximately $500 million, which reveals the significant increase in stock market trading activity in the most recent decade. Both measures of trading activity, volume and turnover, have significantly increased during 1980-2010, which was displayed in *Figures 1* and *2* in Section 4.2.

The following *Figures 4* and *5* display innovations in market liquidity measures volume and turnover throughout January 1980 - December 2010. Turnover has significantly higher shocks in the latter half of the sample period.

**Figure 4**
**Innovations in Monthly Trading Volume**
**January 1980 - December 2010**

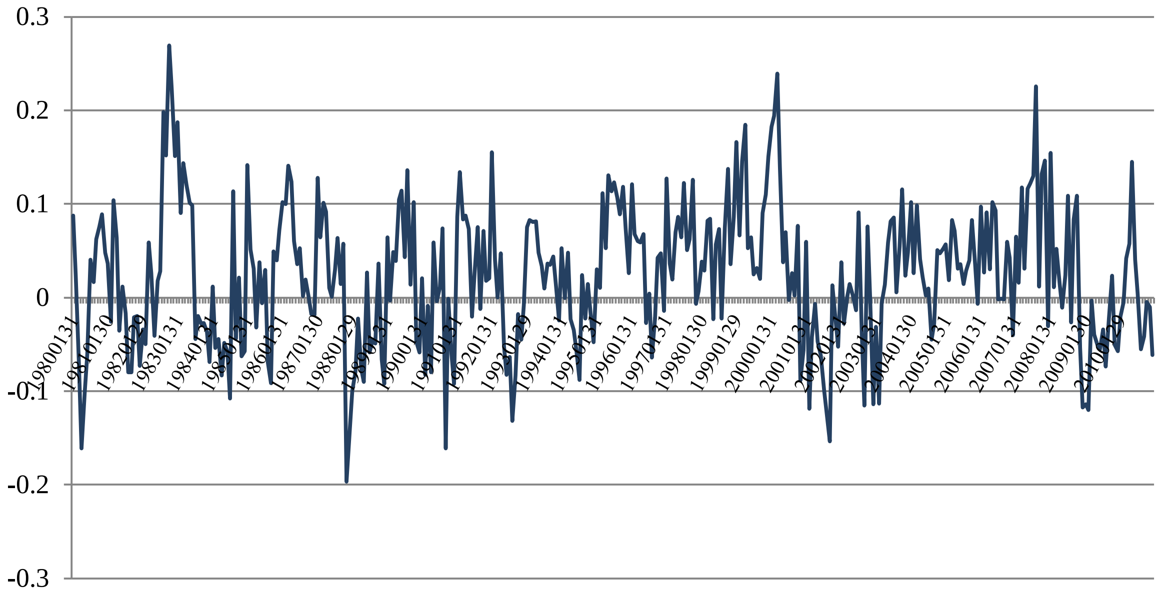


**Figure 4** Innovations in the natural logarithm of average monthly trading volume per stock from January 1980 to December 2010. Data include NYSE, AMEX and Nasdaq listed stocks.

**Figure 5**
**Innovations Monthly Stock Turnover**
**January 1980 - December 2010**

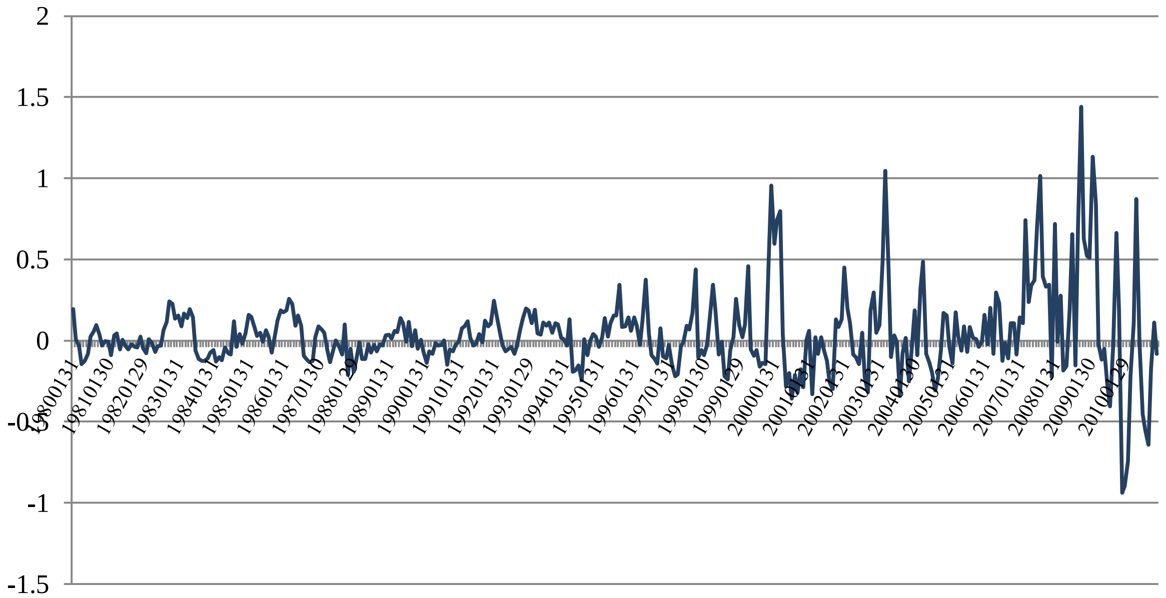


**Figure 5** Innovations in the average monthly stock turnover from January 1980 to December 2010. Data include NYSE, AMEX and Nasdaq listed stocks.

*Table 4* presents cross-correlations of variables used in liquidity timing regressions. Market excess returns have statistically significant correlation of 0.49 with the return on the Barclays US High-Yield Corporate Index (denoted CR). The correlation between the high yield index and Barclays US Aggregate Bond Index (denoted FI) is also high and significant at 0.46. Multicollinearity could complicate statistical inference, as it tends to inflate standard errors of regression coefficients. However, the results presented in Section 5.1 show that this is not a relevant concern.

All of the market liquidity measures display positive and significant correlation with each other: turnover and trading volume have a correlation of 0.44, volume and Sadka 0.24 and turnover and Sadka 0.16. Trading volume and the Sadka liquidity measure both have a positive and statistically significant correlation with market excess returns (0.26 and 0.12 respectively). Interestingly, turnover has slightly negative, although insignificant, correlation with market returns.

**Table 4**
**Cross-correlations of Regression Variables**

Cross-correlations of explanatory regression variables and market liquidity measures. *t*-statistics for correlation estimates are reported in parentheses. Correlations are calculated from monthly observations ranging from January 1980 to December 2010. Data for the Sadka (2006) permanent-variable liquidity measure ranges from April 1983 to December 2008. $R_m$ denotes the market excess return over the 1-month T-Bill rate, SMB, HML and UMD are the Fama-French returns for size, value and momentum strategies, FI denotes return on the Barclays US Aggregate Bond Index and CR the return on the Barclays US High-Yield Corporate Index. Sadka PV, VOL and TO denote the Sadka permanent-variable liquidity measure, average stock market trading volume and stock market turnover respectively. ** and * denote statistical significance at the 1% and 5% levels, respectively.

| | $R_m$ | SMB | HML | UMD | FI | CR | Sadka PV | VOL | TO |
|---|---|---|---|---|---|---|---|---|---|
| $R_m$ | 1.000 | | | | | | | | |
| | - | | | | | | | | |
| SMB | 0.230** | 1.000 | | | | | | | |
| | (4.55) | - | | | | | | | |
| HML | -0.345** | -0.325** | 1.000 | | | | | | |
| | (-7.07) | (-6.61) | - | | | | | | |
| UMD | -0.119* | 0.061 | -0.180** | 1.000 | | | | | |
| | (-2.31) | (1.17) | (-3.51) | - | | | | | |
| FI | 0.176** | -0.122* | 0.013 | -0.002 | 1.000 | | | | |
| | (3.43) | (-2.37) | (0.25) | (-0.04) | - | | | | |
| CR | 0.493** | 0.213** | -0.004 | -0.339** | 0.466** | 1.000 | | | |
| | (10.9) | (4.18) | (-0.07) | (-6.93) | (10.1) | - | | | |
| Sadka PV | 0.120* | -0.138** | -0.024 | -0.129* | 0.048 | -0.189** | 1.000 | | |
| | (2.32) | (-2.67) | (-0.45) | (-2.49) | (0.93) | (-3.69) | - | | |
| VOL | 0.255** | 0.075 | -0.207** | -0.010 | -0.031 | -0.040 | 0.236** | 1.000 | |
| | (5.06) | (1.43) | (-4.07) | (-0.19) | (-0.58) | (-0.76) | (4.67) | - | |
| TO | -0.056 | 0.074 | -0.253** | 0.029 | -0.038 | -0.163** | 0.155** | 0.438** | 1.000 |
| | (-1.08) | (1.41) | (-5.02) | (0.56) | (-0.72) | (-3.17) | (3.02) | (9.37) | - |

## 4.5 Regressions

I start from the following four-factor model in explaining the time series of mutual fund returns:

$$R_{f,t} = \alpha_f + \beta_{f,m}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \varepsilon_{f,t} \tag{4}$$

$R_{f,t}$ is the fund's excess return in month $t$, $R_{m,t}$ is the month-$t$ excess return of the CRSP value-weighted market portfolio and $SMB_t$, $HML_t$, and $UMD_t$ are the month-$t$ returns on the Fama-French factor mimicking portfolios for size, book-to-market and one-year momentum in stock returns.

I then use the first-order Taylor series expansion to express market beta as a linear function of market liquidity in excess of its time-series average:

$$\beta_{f,m,t} = \beta_{f,m,0} + \gamma_f(L_{m,t} - \overline{L}_m) \tag{5}$$

where $L_{m,t}$ is the month-$t$ market liquidity measure, $\overline{L}_m$ is the time-series average of the market liquidity measure and $\beta_{f,m,0}$ is the fund beta in absence of liquidity timing ability. This specification follows previous timing literature (e.g. Ferson and Schadt, 1996; Busse, 1999; Cao et al., 2010). *Equation (5)* approximates how the market exposure of a mutual fund varies with market liquidity.

Substituting *Equation (5)* into *Equation (4)* gives the five-factor liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \gamma_f(L_{m,t} - \overline{L}_m)\, R_{m,t} + \varepsilon_{f,t} \tag{6}$$

where $\gamma_f$ measures the liquidity timing ability of a mutual fund manager. A significant, positive liquidity timing coefficient $\gamma_f$ implies that a fund has higher (lower) market exposure when aggregate market liquidity is higher (lower). In other words, the mutual fund manager is able to increase (reduce) exposure prior to increases (decreases) in liquidity.

Since my sample includes all types of funds except index funds, I also include factors for fixed income returns and credit risk in the liquidity timing regression. *FI* is the factor for fixed income (Barclays US Aggregate Bond Index) and *CR* the factor for credit risk (Barclays High-Yield Corporate Index). Thus the final liquidity timing model is defined as follows:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t \tag{7}$$

$$+ \beta_{CR,f}CR_t + \gamma_{m,p}(L_{m,t} - \overline{L}_m)\, R_{m,t} + \varepsilon_{f,t}$$

I use *Equation (7)* and estimate liquidity timing coefficients for equally weighted portfolios of aggressive growth, growth and growth and income funds respectively. I also run the tests on the entire sample of 21,500 actively managed US mutual funds that have at least 24 consecutive return observations. I use standard OLS and Newey-West heteroschedasticity and autocorrelation consistent standard errors with five lags to estimate the model in all tests that I perform.

# 5 Results

## 5.1 Cross-sectional Differences in Liquidity Timing Ability

To test whether funds' investment styles are connected with liquidity timing ability, I divide the sample funds into three categories: aggressive growth, growth, and growth and income[5]. Grouping the funds follows the classification in CSW (2010), where fund classes are determined by Wiesenberger, Lipper and Strategic Insight objective codes available in the CRSP Mutual Fund database[6]. The following sections present results for liquidity timing tests performed with different liquidity proxies and fund groups.

### *5.1.1 Sadka Liquidity Tests*

*Table 5* presents results for liquidity timing regressions using the Sadka (2006) permanent-variable liquidity measure as the measure of market liquidity. All three fund groups and all 21,500 funds combined have positive liquidity timing coefficients that are significant at the 1% level. Coefficients for aggressive growth, growth, and growth and income funds are 4.92, 4.57 and 2.88 respectively. The timing coefficient for all funds is approximately 2.26. Measured as change in equity exposure (fund beta in the absence of timing ability, $\beta_{f,m,0}$), aggressive growth funds exhibit the strongest liquidity timing ability: prior to a one-standard-deviation increase in liquidity, aggressive funds increase equity beta by approximately 5.70%[7]. Growth funds show the second largest adjustment in market exposure with an increase in fund beta of approximately 3.31 %. The corresponding figure for growth and income funds is 3.03%. For the entire US mutual fund sample the adjustment in market exposure amounts to approximately 2.78%.

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[5] A fourth category, income funds, is also available but omitted in the tests I perform. This is because income funds have an equity market correlation of less than 0.3, which makes the liquidity timing model in *Equation (4)* unsuitable for these funds and distorts results. Aggressive growth and growth and income funds on the contrary have correlations with the S&P 500 of approximately 0.6. Growth funds exhibit the highest equity correlation, approximately 0.8.

[6] Aggressive growth funds are those whose Wiesenberger codes are SCG, AGG and MCG, whose Strategic Insight codes are AGG and SCG, or whose Lipper codes are CA, LSE, MR and SG. Growth funds include those with Wiesenberger codes of G, G-S, S-G, GRO, and LTG, Strategic Insight codes of G, GRO, and GMC, or Lipper code of G. Growth and income funds are those with Wiesenberger codes of GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G and GRI, Strategic Insight code of GRI, or Lipper codes of GI and MC.

[7] The absolute change in equity beta is 0.03 (4.92*0.006). Standard deviation and other descriptive statistics for Sadka and other liquidity measures are available in *Table 3*.

These results are very similar to those estimated by CSW (2010), who use the Pastor-Stambaugh liquidity measure and show that aggressive funds are the most able liquidity timers, followed by growth and growth and income funds. CSW also perform tests on income funds, but find no evidence of significant timing ability on their part. R-squared values for the timing regressions suggest that the model is quite a good fit for the growth fund portfolio – adjusted $R^2$ is approximately 0.60. For aggressive growth and growth and income funds adjusted $R^2$ is approximately 0.40 and for all funds 0.34. Growth funds seem to be the most equity oriented, with economically negligible coefficients for the fixed income and credit factors. Aggressive growth and growth and income funds, in contrast, have both statistically and economically significant loadings on the credit and fixed income factors respectively.

### *5.1.1 Trading Volume Liquidity Tests*

*Table 6* presents liquidity timing results for different fund classes using equity market trading volume as the measure of aggregate liquidity. The liquidity timing coefficients are positive for all three fund groups and the aggregate fund sample. Results are also statistically significant for aggressive growth funds and all funds at the 1% level, and for growth funds at the 5% level. However, growth and income funds do not show statistically significant timing ability. Coefficients for the aggressive growth, growth and growth and income portfolios are 0.486, 0.062 and 0.021, respectively. The timing coefficient for all funds is approximately 0.029. Measured as relative change in fund equity market exposure, aggressive funds adjust beta by approximately 52.4%, which is an economically highly significant result. Timing ability is much more modest for growth funds, which only increase market exposure by approximately 4.0% prior to a one-standard-deviation increase in aggregate market trading volume. For the entire US mutual fund sample, relative adjustment in market exposure amounts to approximately 3.1%.

**Table 5**
**Liquidity Timing Ability – Sadka Permanent-Variable Liquidity Measure**

Time-series regression results of the seven-factor liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t + \gamma_{m,p}(L_{m,t}-\overline{L}_m)\, R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the Sadka (2006) market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use standard OLS to estimate the model. $t$-statistics are listed in parentheses below regression coefficients. Results are reported for equally weighted portfolios of aggressive growth, growth, growth and income and all funds, respectively. The data range from May 1983 to December 2008. ** and * indicate significance at the 1% and 5% levels.

| Fund Group | $\alpha_f$ | $\beta_{f,m,0}$ | $\beta_{SMB,f}$ | $\beta_{HML,f}$ | $\beta_{UMD,f}$ | $\beta_{FI,f}$ | $\beta_{CR,f}$ | $\gamma_{m,p}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Aggressive Growth | -0.001** | 0.521** | 0.095** | 0.039** | 0.022** | 0.045** | 0.146** | 4.915** | 0.371 |
| | (-6.82) | (116.9) | (22.0) | (7.41) | (7.40) | (3.27) | (17.1) | (8.96) | |
| Growth | -0.001** | 0.835** | 0.074** | 0.032** | 0.000 | -0.017 | 0.024** | 4.568** | 0.604 |
| | (-8.13) | (210.5) | (16.2) | (6.29) | (0.07) | (-1.56) | (3.56) | (12.8) | |
| Growth & Income | -0.001** | 0.575** | 0.144** | 0.097** | 0.000 | 0.118** | 0.009 | 2.879** | 0.377 |
| | (-11.7) | (210.8) | (52.6) | (29.5) | (0.02) | (14.7) | (1.82) | (9.43) | |
| All Funds | -0.001** | 0.492** | 0.083** | 0.049** | 0.001 | 0.105** | 0.093** | 2.261** | 0.344 |
| | (-27.2) | (559.2) | (90.2) | (45.2) | (1.85) | (41.7) | (60.8) | (26.1) | |

**Table 6**
**Liquidity Timing Ability – Trading Volume**

Time-series regression results of the seven-factor liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t + \gamma_{m,p}(L_{m,t}-\overline{L}_m)\,R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the trading volume market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use standard OLS to estimate the model. $t$-statistics are listed in parentheses below regression coefficients. Results are reported for equally weighted portfolios of aggressive growth, growth, growth and income and all funds, respectively. The data range from January 1980 to December 2010. ** and * indicate significance at the 1% and 5% levels.

| Fund Group | $\alpha_f$ | $\beta_{f,m,0}$ | $\beta_{SMB,f}$ | $\beta_{HML,f}$ | $\beta_{UMD,f}$ | $\beta_{FI,f}$ | $\beta_{CR,f}$ | $\gamma_{m,p}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Aggressive Growth | -0.001** | 0.508** | 0.089** | 0.033** | 0.008** | 0.026 | 0.196** | 0.486** | 0.389 |
| | (-8.11) | (125.2) | (21.7) | (7.17) | (2.90) | (1.92) | (26.7) | (12.8) | |
| Growth | -0.001** | 0.855** | 0.074** | 0.025** | 0.004 | -0.030** | 0.045** | 0.062* | 0.652 |
| | (-9.98) | (298.7) | (19.1) | (6.61) | (1.55) | (-3.55) | (8.37) | (2.23) | |
| Growth & Income | -0.001** | 0.576** | 0.143** | 0.087** | 0.002 | 0.112** | 0.042** | 0.021 | 0.399 |
| | (-9.53) | (241.1) | (55.6) | (31.0) | (0.92) | (15.4) | (9.58) | (0.93) | |
| All Funds | 0.000** | 0.512** | 0.083** | 0.059** | -0.001 | 0.100** | 0.111** | 0.029** | 0.374 |
| | (-22.4) | (703.4) | (96.4) | (67.7) | (-1.87) | (43.5) | (85.7) | (4.11) | |

Trading volume tests add to the evidence that aggressive growth funds seem to exhibit the strongest liquidity timing skill with the highest adjustment in fund market exposure prior to changes in aggregate liquidity. Results are also qualitatively similar to those reported by CSW, although the evidence of aggressive growth funds' timing ability is much stronger in magnitude when liquidity is measured by trading volume. $R^2$ values for trading volume regressions are very close to those of the turnover liquidity tests: approximately 0.65 for growth funds and 0.40 for aggressive growth, growth and income and all funds. Again, aggressive growth funds have heavy loading on the credit risk factor, while growth and income funds load heavily on the fixed income factor.

### *5.1.1 Turnover Liquidity Tests*

Results for the turnover liquidity timing tests are presented in *Table 7*. Again, all three fund groups and the aggregate fund sample exhibit positive and significant liquidity timing ability. Timing coefficients for aggressive growth, growth, and growth and income funds are 0.107, 0.042 and 0.011 respectively. For the entire US mutual fund portfolio the timing coefficient is approximately 0.042. All coefficients are significant at the 1% level. Measured as relative change in fund beta in the absence of timing ability ($\beta_{f,m,0}$), aggressive growth funds increase equity market exposure by approximately 14.1% prior to a one-standard-deviation in liquidity. For growth and growth and income funds this adjustment amounts to approximately 4.44% and 1.72%, respectively. The adjustment for funds on an aggregate level is 7.46%.

As with the Sadka liquidity measure, turnover timing tests yield similar results as those that CSW (2010) present for US equity funds. However, turnover tests produce a much higher estimate of adjustment in market exposure for aggressive funds than the Sadka permanent-variable liquidity measure. Also, differences in fund groups' timing ability are more pronounced with the turnover liquidity measure, as growth and income funds show only negligible (although significant and positive) adjustment in fund beta. As with Sadka liquidity timing tests, adjusted $R^2$ values for aggressive growth, growth, growth and income and all funds are 0.40, 0.65, 0.40 and 0.40 respectively. Aggressive growth funds have a heavy loading on the credit risk factor and growth and income funds on the fixed income factor, while growth funds have the highest equity beta.

**Table 7**
**Liquidity Timing Ability – Turnover**

Time-series regression results of the seven-factor liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t + \gamma_{m,p}(L_{m,t}-\overline{L}_m)\,R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the turnover market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use standard OLS to estimate the model. $t$-statistics are listed in parentheses below regression coefficients. Results are reported for equally weighted portfolios of aggressive growth, growth, growth and income and all funds, respectively. The data range from January 1980 to December 2010. ** and * indicate significance at the 1% and 5% levels.

| Fund Group | $\alpha_f$ | $\beta_{f,m,0}$ | $\beta_{SMB,f}$ | $\beta_{HML,f}$ | $\beta_{UMD,f}$ | $\beta_{FI,f}$ | $\beta_{CR,f}$ | $\gamma_{m,p}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Aggressive Growth | -0.001** | 0.515** | 0.084** | 0.019** | 0.012** | 0.043** | 0.170** | 0.107** | 0.390 |
| | (-4.76) | (131.3) | (20.6) | (4.06) | (4.21) | (3.21) | (22.8) | (15.7) | |
| Growth | -0.001** | 0.852** | 0.074** | 0.017** | 0.003 | -0.026** | 0.036** | 0.042** | 0.653 |
| | (-8.21) | (298.3) | (19.3) | (4.60) | (1.15) | (-3.18) | (6.58) | (8.12) | |
| Growth & Income | -0.001** | 0.576** | 0.143** | 0.085** | 0.001 | 0.113** | 0.039** | 0.011** | 0.399 |
| | (-9.30) | (246.9) | (55.6) | (29.8) | (0.82) | (15.5) | (8.85) | (2.67) | |
| All Funds | 0.000** | 0.508** | 0.084** | 0.052** | -0.003** | 0.101** | 0.101** | 0.042** | 0.375 |
| | (-16.5) | (700.5) | (97.2) | (58.5) | (-5.75) | (43.6) | (75.7) | (34.9) | |

### *Possible Statistical Concerns*

Correlations between the explanatory regression variables are presented in *Table 4*. The two variables measuring fixed income and credit risk exposure, $FI_t$ and $CR_t$, are quite highly correlated: the estimated correlation coefficient is 0.47 with a *t*-statistic 10.1. $CR_t$ also has a correlation of 0.49 with market excess returns (*t*-statistic 10.9). Multicollinearity could result in large standard errors for the estimated regression coefficients, which would affect inference about statistical significance. Clearly this should not be the case here, as the model I use produces highly significant regression coefficients. Nevertheless, I perform all previously presented tests omitting both $FI_t$ and $CR_t$ one at a time. The results are essentially unchanged: the interpretation of liquidity timing ability remains unaffected, whilst the remaining risk factors experience only slight changes[8]. In the following analysis I choose to include all of the factors in my model, as presented in *Equation (7)*.

### *5.1.1 Controlling for a Passive Liquidity Timing Effect*

Next I test for the possibility that the previously reported results indicating significant positive liquidity timing ability are only due to a "passive" timing effect, i.e. not attributable to active fund management. This could result from the betas of financial assets responding to changes in market liquidity – in this case even an index tracking strategy could give the appearance of active liquidity timing. If an index portfolio demonstrates ability to time market liquidity, the documented relationships between market liquidity measures and fund systematic risk could be due to a passive timing effect rather than fund managers' timing ability.

To test for a passive timing effect I compare the liquidity timing coefficients for US equity index funds with regression results from the previously reported liquidity timing tests on actively managed mutual funds. Index funds are identified by the index fund flag provided by the CRSP US Mutual Fund Database. The data consist of altogether 482 equity index funds and 34,201 monthly return observations. I run the following five-factor model:

$$R_{index,t} = \alpha + \beta_{m,0}R_{m,t} + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t \qquad (8)$$

$$+ \gamma_{index}(L_{m,t} - \overline{L}_m)\, R_{m,t} + \varepsilon_{f,t}$$

[8] I try other regression model specifications as well, altering the number of risk factors, but inference of timing ability remains materially unchanged.

Results for the passive liquidity timing test are reported in *Table 8*. Timing coefficients for both the Sadka measure and trading volume tests are positive and statistically significant. With turnover, the timing coefficient is close to zero. Specifically, timing coefficients using the Sadka measure, trading volume and turnover are 0.258, 0.015 and -0.006 respectively with *t*-statistics of 43.8, 35.3 and -59.2. All of the coefficients are remarkably smaller in magnitude than for any of the portfolios of actively managed funds, as reported in *Table 5*. The economic significance of the index funds' timing coefficients is negligible. This suggests that the previously reported positive and significant liquidity timing coefficients are not simply due to a passive adjustment in the systematic risk of fund holdings.

**Table 8**
**Controlling for a Passive Liquidity Timing Effect**

Time-series regression results of the five-factor liquidity timing model:

$$R_{index,t} = \alpha_f + \beta_{m,0}R_{m,t} + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \gamma_{index}(L_{m,t} - \overline{L}_m)\, R_{m,t} + \varepsilon_{f,t}$$

where $R_{index,t}$ denotes the month-*t* excess return on US equity index funds, $R_{m,t}$ is the month-*t* return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-*t* Fama-French factors for size, value and momentum strategies respectively, $L_{m,t}$ is the market liquidity measure for month-*t* and $\overline{L}_m$ is the time-series average of market liquidity measures. I use standard OLS to estimate the model. *t*-statistics are reported in parentheses below regression coefficients. Results are reported for the Sadka (2006) permanent-variable liquidity measure, trading volume and turnover, respectively. The data range from January 1980 to December 2010 and consist of altogether 482 individual index funds. ** indicates significance at the 1% level.

| Measure | $\alpha$ | $\beta_{m,0}$ | $\beta_{SMB}$ | $\beta_{HML}$ | $\beta_{UMD}$ | $\gamma_{index}$ | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|
| Sadka PV | -0.001** | 1.071** | -0.004** | 0.069** | 0.009** | 0.258** | 0.635 |
| | (-45.5) | (141.6) | (-4.85) | (63.9) | (14.3) | (43.8) | |
| Volume | -0.001** | 1.045** | 0.024** | 0.074** | -0.025** | 0.015** | 0.623 |
| | (-37.7) | (152.5) | (26.6) | (76.3) | (-43.8) | (35.3) | |
| Turnover | 0.000** | 1.039** | 0.021** | 0.048** | -0.028** | -0.006** | 0.623 |
| | (-11.5) | (149.2) | (22.9) | (48.1) | (-49.3) | (-59.2) | |

The next part summarizes results from the main analysis of US mutual funds' liquidity timing ability. The following sections present results on the relationship between fund characteristics and liquidity timing, and robustness checks regarding the observed positive liquidity timing ability.

### 5.1.2 *Summary of Liquidity Timing Results*

*Table 9* presents a summary of the main analysis of mutual funds' liquidity timing. Panels A, B and C report the absolute and relative changes in average fund beta for the four fund portfolios and the three liquidity measures. Changes in fund beta are estimated in case of a one-standard-deviation increase in market liquidity, ceteris paribus. The tests produce highly significant results, which indicate positive timing ability throughout the sample. There are clearly cross-sectional differences in liquidity timing with respect to fund riskiness: aggressive growth funds show strongest liquidity timing skill.

**Table 9**
**Summary of Liquidity Timing Results**

Summary of the results of liquidity timing tests performed on actively managed US mutual funds. Data range from January 1980 to December 2010. Results are reported for equally weighted portfolios of aggressive growth, growth, growth and income and all funds, respectively. The first column reports absolute change in average fund beta in case of a one-standard-deviation increase in aggregate liquidity. The second column reports the relative change in average fund beta with respect to beta in the absence of liquidity timing ability. The third column reports corresponding *t*-statistics of the liquidity timing coefficients. Panels A, B and C present results for tests using the Sadka (2006) permanent-variable liquidity measure, trading volume and turnover, respectively. ** denotes significance at the 1% level.

**Panel A. Sadka Liquidity Measure**

| Fund Group | ΔBeta | ΔBeta% | *t*-statistic |
|---|---|---|---|
| Aggressive Growth | 0.030 | 5.70 % | 8.96** |
| Growth | 0.028 | 3.31 % | 12.82** |
| Growth & Income | 0.017 | 3.03 % | 9.43** |
| All Funds | 0.014 | 2.78 % | 26.14** |

**Panel B. Trading Volume**

| Fund Group | ΔBeta | ΔBeta% | *t*-statistic |
|---|---|---|---|
| Aggressive Growth | 0.266 | 52.38 % | 12.8** |
| Growth | 0.034 | 3.98 % | 2.23** |
| Growth & Income | 0.012 | 2.00 % | 0.93 |
| All Funds | 0.016 | 3.09 % | 4.11** |

**Panel C. Turnover**

| Fund Group | ΔBeta | ΔBeta% | *t*-statistic |
|---|---|---|---|
| Aggressive Growth | 0.097 | 14.12 % | 15.71** |
| Growth | 0.038 | 4.44 % | 8.12** |
| Growth & Income | 0.010 | 1.72 % | 2.67** |
| All Funds | 0.038 | 7.46 % | 34.99** |

## 5.2 Fund Characteristics and Liquidity Timing

In the previous section I document positive liquidity timing ability for funds on average, but also variation between fund portfolios: most tests suggest that aggressive growth funds are the most able liquidity timers, followed by growth funds. This suggests that the riskiness of the fund's investment strategy is somehow related to liquidity timing success. In the following I test whether there are other fund characteristics associated with liquidity timing.

To test for a cross-sectional relationship between fund characteristics and timing ability, I estimate the following regression for all funds and within each of the three fund categories:

$$\hat{\gamma}_f = \alpha_f + \beta_{AGE} AGE_f + \beta_{EXP} EXP_f + \beta_{TR} TR_f + \beta_{FLOW} FLOW_f + \beta_{FVOL} FVOL_f + \varepsilon_f \qquad (9)$$

where $\hat{\gamma}_f$ is the liquidity timing coefficient measured for each fund with at least 24 monthly return observations, $AGE_f$ is the fund's age in years and $EXP_f$, $TR_f$, $FLOW_f$, and $FVOL_f$ are the time-series averages of the fund's expense ratio, asset turnover, normalized fund flow and fund flow standard deviation, respectively. This fund characteristics data is available in the CRSP Survivor-Bias-Free US Mutual Fund Database for 4,429 funds out of the 21,500 funds included in the entire sample.

*Table 10* presents the cross-correlations of fund characteristics. Fund size and age show positive and significant correlation (0.26, *t*-statistic 17.9), which seems intuitive. Fund size is also positively correlated (0.38, *t*-statistic 27.5) with the standard deviation of normalized fund flows. Fund flows and flow volatility are significantly negatively correlated (-0.51, *t*-statistic -39.6), which indicates that funds with smaller average investor flows experience greater fluctuation in flows.

*Table 11* presents results of the tests of cross-sectional differences in fund liquidity timing ability. Looking at all three tests, fund age seems to be an insignificant factor in timing ability. All of the three age coefficients are very small in magnitude, and only one of them is statistically significant. Considering that funds may benefit from the ability to time liquidity, and that aspect might improve performance and attract investors, a positive relationship between timing ability and fund age would seem natural. My data, however, does not support this hypothesis: age coefficients are statistically insignificant. As shown in *Table 1*, aggressive growth funds have the lowest average age, but they are also found to be the best liquidity timers. In this respect the results seem somewhat coherent.

**Table 10**
**Cross-correlations of Fund Characteristics**

Cross-correlations of fund characteristics used to estimate cross-sectional differences in funds' liquidity timing ability. Data come from the CRSP Survivor-Bias Free US Mutual Fund Database. Fund age is defined as years between the first and last return dates in the database. Expense ratios and turnover data are annual percentages. Fund size is measured as TNA in dollar millions. Fund flows are calculated as the change in monthly TNA adjusting for fund returns, standardized by dividing by fund TNA and averaged across time for each fund. Fund flow standard deviations are calculated from monthly flow data. Correlations are estimated from altogether 4,429 fund observations. *t*-statistics are reported in parentheses. ** and * denote significance at the 1% and 5% levels, respectively.

| | Age | Exp. Ratio | Turnover | Size | Flow | Flow Std.dev. |
|---|---|---|---|---|---|---|
| Age | 1.000 | | | | | |
| | - | | | | | |
| Exp. Ratio | -0.094** | 1.000 | | | | |
| | (-6.26) | - | | | | |
| Turnover | -0.064** | 0.099** | 1.000 | | | |
| | (-4.28) | (6.58) | - | | | |
| Size | 0.261** | -0.074** | -0.034* | 1.000 | | |
| | (17.9) | (-4.94) | (-2.27) | - | | |
| Flow | -0.009 | -0.035* | 0.003 | 0.175** | 1.000 | |
| | (-0.60) | (-2.31) | (0.16) | (11.7) | - | |
| Flow Std.dev. | 0.089** | -0.042* | -0.029 | 0.382** | -0.512** | 1.000 |
| | (5.91) | (-2.78) | (-1.90) | (27.5) | (-39.6) | - |

Expense ratio, on the contrary, has a strong positive relation with timing ability. That is, funds that are more skilled in liquidity timing charge higher fees. This result is intuitively appealing: if funds are able to provide investors with a liquidity hedge that is valuable, they can charge higher fees. The result is also consistent with the fact that aggressive growth funds charge the highest fees (see *Table 1*).

Tests on the Sadka liquidity timing coefficients suggest that fund turnover rate is negatively related to timing ability – funds that are successful in timing trade less frequently. For the other two liquidity measures, however, turnover does not produce significant coefficients[9]. This is at odds with the fact that the best liquidity timers, aggressive growth funds, have the highest turnover rates. Also, it would seem natural that liquidity timing funds need frequent adjustment in fund holdings in order to adjust to changing expectations of future liquidity.

[9] Alternative regression model specifications all suggest the same: fund turnover rate is negatively related to timing ability. Coefficients are either negative or insignificant.

This kind of a relationship between turnover rate and timing ability is not evident in the tests I perform.

All coefficients on normalized fund flows are positive, but only one of them is significant. Gruber (1996) discusses the selection ability of mutual fund investors, that is, whether investors are smart ex ante and invest in fund that perform better. Considering that liquidity timing could be a valuable service for fund investors, timing ability could attract investors and thereby increase fund flows. The evidence of a so called smart money effect is weak in my sample of funds, although not totally dismissible. On the other hand, a negative relationship between flows and timing ability could result in a false impression of timing ability: during periods of lower liquidity the reduction in systematic risk caused by fund redemptions could look like liquidity timing.

The standard deviation of fund flows and liquidity timing ability are be positively related in the Sadka and trading volume tests. This is somewhat counterintuitive, as one would expect that funds with lower flow volatility are less affected by investor flows and thus better able to implement liquidity timing and other investment strategies. Then again, this result is consistent with the observation that aggressive funds, which show highest liquidity timing ability, have the highest fund flow volatility.

To sum, my results suggest that expense ratio and fund flow volatility are positively related to liquidity timing ability. This means that successful liquidity timers charge higher fees and experience more variation in investor demand. There is also weak evidence of a positive relationship between fund flows and timing skill. Evidence regarding fund size and age is either mixed or insignificant. For some reason, turnover is negatively related to timing ability – fund managers with timing skill seem to trade less frequently.

## Table 11
## Cross-sectional Relationship Between Fund Characteristics and Liquidity Timing

Cross-sectional regression results of liquidity timing coefficients on fund characteristics:

$$\hat{\gamma}_f = \alpha_f + \beta_{AGE}AGE_f + \beta_{SIZE}SIZE_f + \beta_{EXP}EXP_f + \beta_{TR}TR_f + \beta_{FLOW}FLOW_f + \beta_{FVOL}FVOL_f + \varepsilon_f$$

where $\hat{\gamma}_f$ is the liquidity timing coefficient of fund *f* estimated from the liquidity timing model presented in Equation (7), $AGE_f$ is the fund's age in years, $SIZE_f$ is the natural logarithm of fund TNA in dollar millions, $EXP_f$ is the fund's annual expense ratio in percentages, $TR_f$ is the fund's annual turnover ratio in percentages, and $FLOW_f$ and $FVOL_f$ are the fund's normalized monthly flow and flow standard deviation, respectively. Characteristics data are averaged across time for each fund. All fund characteristics data come from the CRSP Survivor-Bias Free US Mutual Fund Database. I only include funds that have at least 24 consecutive monthly return observations available during the period from January 1980 to December 2010. Results are reported for timing coefficients $\hat{\gamma}_f$ estimated with the Sadka (2006) permanent-variable liquidity measure, trading volume and turnover in Panels A, B and C, respectively. *t*-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

**Panel A. Sadka Liquidity Measure**

| $\alpha_f$ | $\beta_{AGE}$ | $\beta_{SIZE}$ | $\beta_{EXP}$ | $\beta_{TR}$ | $\beta_{FLOW}$ | $\beta_{FVOL}$ | $R^2$ | Nr of obs. |
|---|---|---|---|---|---|---|---|---|
| -4.844*** | 0.008 | 0.450** | 29.51*** | -0.723*** | 5.067 | 1.665** | 0.015 | 3 392 |
| (-3.89) | (0.26) | (2.00) | (5.88) | (-3.38) | (0.73) | (2.14) | | |

**Panel B. Trading Volume**

| $\alpha_f$ | $\beta_{AGE}$ | $\beta_{SIZE}$ | $\beta_{EXP}$ | $\beta_{TR}$ | $\beta_{FLOW}$ | $\beta_{FVOL}$ | $R^2$ | Nr of obs. |
|---|---|---|---|---|---|---|---|---|
| -0.209** | -0.002 | 0.019 | 27.32*** | -0.004 | 0.821* | 0.090* | 0.017 | 3 756 |
| (-2.33) | (-0.96) | (1.17) | (7.69) | (-0.28) | (1.72) | (1.69) | | |

**Panel C. Turnover**

| $\alpha_f$ | $\beta_{AGE}$ | $\beta_{SIZE}$ | $\beta_{EXP}$ | $\beta_{TR}$ | $\beta_{FLOW}$ | $\beta_{FVOL}$ | $R^2$ | Nr of obs. |
|---|---|---|---|---|---|---|---|---|
| 0.085*** | -0.001 | -0.015*** | 7.005*** | 0.005 | 0.078 | -0.003 | 0.015 | 3 756 |
| (2.86) | (-1.33) | (-2.81) | (5.96) | (0.91) | (0.50) | (-0.19) | | |

## 5.3 Robustness Checks

### 5.3.1 Controlling for a Liquidity Risk Factor

As explained in Section 2.5 of the literature review, finance research has identified liquidity risk as an important determinant of stock returns. The relationship between mutual funds' liquidity risk exposure and returns, on the other hand, has only recently emerged as a research topic. Dong, Feng and Sadka (2011) present evidence that liquidity risk is significant in determining fund returns. They argue that funds loading on liquidity risk subsequently outperform those with lower liquidity risk exposure. Nonetheless, the topic is still quite thinly examined in finance literature.

To test whether an omitted liquidity risk factor could be driving the liquidity timing results presented earlier, I add the Pastor-Stambaugh (2003) value-weighted traded liquidity factor as an explanatory variable in the timing tests. The traded liquidity factor measures the return difference between value-weighted high and low historical liquidity beta portfolios. It is possible that an omitted liquidity risk factor in fund returns manifests itself in the liquidity timing coefficients, so that the observed timing coefficients do not measure actual timing ability. I use the three liquidity measures and run the following regression on all three fund groups and the entire fund sample:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t \tag{10}$$

$$+ \beta_{CR,f}CR_t + \beta_{LIQ,f}LIQ_t + \gamma_{m,p}(L_{m,t} - \overline{L}_m)R_{m,t} + \varepsilon_{f,t}$$

$R_{f,t}$ denotes the fund $f$ return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. $LIQ_t$ denotes the Pastor-Stambaugh (2003) traded liquidity risk factor for month $t$. Regression results are summarized in *Table 12*.

Comparison with the results of the main analysis in Section 5.1 reveals that the estimated liquidity timing ability remains practically unchanged. In the case of the Sadka measure and trading volume, adding a liquidity risk factor in the timing test slightly increases the magnitude of the timing coefficients for the three fund portfolios. Timing coefficients for aggressive growth, growth, growth and income and all funds are 5.04, 4.87, 3.25 and 2.07 respectively, and they all remain significant at the 1% level.[10] With trading volume, timing coefficients for aggressive growth, growth, growth and income and all funds are 0.500, 0.094, 0.031 and 0.020, respectively, and significant for aggressive growth, growth and all funds.[11] With turnover as the market liquidity measure, results remain practically unchanged[12].

Almost all of the liquidity risk coefficients $\beta_{LIQ,f}$ are negative and negligible in magnitude, although statistically significant. Only the aggregate fund sample has positive and significant liquidity risk coefficients. The impact of liquidity risk on fund returns appears economically insignificant. With an average monthly return of approximately 0.65% on the high-minus-low-liquidity portfolio (Pastor-Stambaugh value-weighted, traded liquidity factor), the effect on fund return for aggressive, growth, growth and income and all funds would be -0.003%, -0.025%, -0.013% and 0.008%, respectively. These are certainly negligible liquidity risk exposures in an economic sense. Removing the liquidity timing factor $\gamma(L_{m,t} - \overline{L}_m)\ R_{m,t}$ and only testing for the importance of liquidity risk exposure on fund returns does not significantly alter results; coefficients remain insignificant in magnitude. As the focus of my study is not on liquidity risk per se, but on funds' liquidity timing, I leave further discussion of the topic for others.

Overall, the results suggest that the significant positive timing ability observed in Section 5.1 isn't due to an omitted liquidity risk factor in the regression model specification. CSW (2010) conduct similar analysis in their study of funds' liquidity timing and present analogous results: liquidity timing remains materially unchanged after controlling for liquidity risk. They also report that liquidity risk is not useful in explaining mutual fund returns, which is consistent with my results.

[10] In the main analysis in Section 5.1, Sadka timing coefficients for aggressive, growth, growth and income and all funds were 4.92, 4.57, 2.88 and 2.26, respectively.

[11] In the main analysis in Section 5.1, trading volume timing coefficients for aggressive, growth, growth and income and all funds were 0.49, 0.062, 0.021 and 0.029, respectively.

[12] In the main analysis in Section 5.1, turnover timing coefficients for aggressive, growth, growth and income and all funds were 0.107, 0.042, 0.011 and 0.042, respectively.

## Table 12
## Controlling for a Liquidity Risk Factor

Time-series regression results of the liquidity timing model with a liquidity risk factor:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t$$

$$+ \beta_{CR,f}CR_t + \beta_{LIQ,f}LIQ_t + \gamma_{m,p}(L_{m,t} - \overline{L}_m)R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $LIQ_t$ is the Pastor-Stambaugh (2003) value-weighted liquidity risk factor for month-$t$, $L_{m,t}$ is the market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use OLS to estimate the model. Data range from January 1980 to December 2010. Panel A reports liquidity timing coefficients $\gamma_{m,p}$ and Panel B liquidity risk coefficients $\beta_{LIQ,f}$ for equally weighted portfolios of aggressive growth, growth, growth and income and all funds, respectively. *t*-statistics are reported in parentheses. ** and * indicate significance at the 1% and 5% levels respectively.

**Panel A. Liquidity Timing Coefficients $\gamma_{m,p}$**

| | Liquidity Measure | | |
|---|---|---|---|
| Fund Group | Sadka | Trading Volume | Turnover |
| Aggressive Growth | 5.036** | 0.500** | 0.107** |
| | (8.99) | (12.9) | (15.7) |
| Growth | 4.874** | 0.094** | 0.038** |
| | (13.6) | (3.36) | (7.43) |
| Growth & Income | 3.246** | 0.031 | 0.010* |
| | (10.5) | (1.37) | (2.40) |
| All funds | 2.073** | 0.020** | 0.043** |
| | (23.7) | (2.83) | (35.7) |

**Panel B. Liquidity Risk Coefficients $\beta_{LIQ,f}$**

| | Liquidity Measure | | |
|---|---|---|---|
| Fund Group | Sadka | Trading Volume | Turnover |
| Aggressive Growth | -0.005 | -0.008* | 0.003 |
| | (-1.06) | (-2.23) | (0.82) |
| Growth | -0.039** | -0.027** | -0.024** |
| | (-10.6) | (-9.44) | (-8.48) |
| Growth & Income | -0.020** | -0.007** | -0.007** |
| | (-7.95) | (-3.52) | (-3.17) |
| All funds | 0.013** | 0.006** | 0.008** |
| | (16.2) | (8.26) | (11.2) |

### *5.3.2 Controlling for Unusual Liquidity Events*

In the following I test whether omitting two periods of extraordinary liquidity conditions from the analysis affects the results of timing tests. Specifically, I exclude the six-month periods from September 1987 to February 1988 and September 2008 to February 2009 from the main analysis in Section 5.1. The goal is to investigate how significant the fund manager's skills in liquidity management are during times of liquidity conditions that can be considered normal. I base the selection of the two omitted periods on common views about the occurrence of significant market turmoil, rather than any quantitative selection process[13]. The September 1987 market crash marks the start of the first liquidity squeeze period, and September 2008 the escalation of the financial crisis that resulted in a significant decrease in liquidity in the financial markets.

Results from tests omitting the two periods of market turmoil and low liquidity are presented in *Table 13*. The results are conspicuous: omitting both periods reduces the Sadka measure timing coefficients for aggressive growth, growth, and growth and income funds (Panel A, first column) close to zero. These coefficients also loose significance. On the other hand, the timing coefficient for the aggregate mutual fund sample becomes negative: -2.28 with a significant *t*-statistic of -16.4. Trading volume timing coefficients experience changes too: all coefficients remain statistically significant, but only aggressive growth funds continue to exhibit positive timing ability, whereas other groups' timing coefficients turn negative. Confusingly, timing coefficients for the turnover measure remain positive and significant except for the growth and income fund group. The positive timing ability displayed by aggressive growth funds actually strengthens slightly.

The evidence is mixed. Using Sadka and trading volume indicates that during "normal" liquidity conditions, funds exhibit insignificant or negative liquidity timing ability. That is, the positive timing ability discovered in the main analysis is driven by periods of extraordinary market liquidity conditions. One explanation could be that fund managers only actively manage liquidity during periods of low liquidity or market turmoil, but neglect this aspect during normal market conditions.

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[13] Looking at Figures 3, 4 and 5, there are occasional liquidity shocks that stand out throughout the sample period 1980-2010. However, attempting to omit all of these would require a somewhat arbitrary decision about the definition of a sufficiently large liquidity shock to be counted as "a liquidity squeeze". Also, it's more natural to think that liquidity shocks coinciding with significant economic events (such as the financial crisis) have more relevance than individual liquidity spikes that occur during more stable economic conditions.

CSW (2010) conduct similar analysis for US equity funds and find that including the 1987 market crash in the analysis results in much stronger evidence of liquidity timing ability. They conclude that liquidity timing is more valuable during market turmoil as it provides a hedge for fund owners.

Testing with turnover, in contrast, indicates that funds' liquidity timing ability is essentially the same during times of normal liquidity as it is with liquidity squeeze periods included in the analysis. This would suggest that fund managers actively manage the fund's market exposure with respect to changes in liquidity, irrespective of current liquidity conditions. This in turn is somewhat in line with the findings of Cao, Chen, Liang and Lo (2011), who examine hedge funds' liquidity timing ability and conclude that excluding the 2007-2008 financial crisis from the analysis results in even stronger positive estimates of funds' timing skill.

To sum, when liquidity is measured with return reversals and trading volume, it appears that fund managers only engage in liquidity timing during periods of extraordinary liquidity conditions. Turnover timing tests, on the contrary, show consistent timing skill irrespective of market conditions.

# Table 13
## Controlling for Unusual Liquidity Events

Time-series regression results of the liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t$$
$$+ \gamma_{m,p}(L_{m,t} - \overline{L}_m)\, R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ excess return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use OLS to estimate the model. Data range from January 1980 to December 2010. Panel A presents results for tests omitting the 6-month periods from September 1987 to February 1988 and September 2008 to February 2009. Panel B presents results for the entire time period to enable comparison. *t*-statistics are reported in parentheses. ** and * indicate significance at the 1% and 5% levels respectively.

**Panel A. Omitting Liquidity Squeeze Periods**

| | **Liquidity Measure** | | |
|---|---|---|---|
| | Sadka | Trading Volume | Turnover |
| Aggressive Growth | 0.357 | 0.425** | 0.155** |
| | (0.50) | (10.3) | (15.7) |
| Growth | -0.990 | -0.069** | 0.038** |
| | (-1.59) | (-2.15) | (4.84) |
| Growth & Income | -0.035 | -0.089** | 0.010 |
| | (-0.08) | (-3.63) | (1.62) |
| All funds | -2.277** | -0.136** | 0.016** |
| | (-16.4) | (-17.3) | (8.86) |

**Panel B. Entire Time Period**

| | **Liquidity Measure** | | |
|---|---|---|---|
| | Sadka | Trading Volume | Turnover |
| Aggressive Growth | 4.915** | 0.486** | 0.107** |
| | (8.96) | (12.8) | (15.7) |
| Growth | 4.568** | 0.062* | 0.042** |
| | (12.8) | (2.23) | (8.12) |
| Growth & Income | 2.878** | 0.021 | 0.011** |
| | (9.43) | (0.93) | (2.67) |
| All funds | 2.261** | 0.029** | 0.042** |
| | (26.1) | (4.11) | (34.9) |

### 5.3.3 Controlling for Market and Volatility Timing

Next I test for the possibility that the observed positive liquidity timing ability of US mutual funds could be due to market timing or volatility timing that manifests itself through the liquidity timing coefficients. This is a relevant concern: Acharya and Pedersen (2005) document a positive relationship between market liquidity and contemporaneous returns, and Pastor and Stambaugh (2003) find evidence of negative correlation between liquidity and market volatility.

I test for liquidity timing whilst controlling for market and volatility timing. A fund's market beta is then expressed as a function of market excess return, market volatility and market liquidity. The liquidity timing model is as follows:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t \qquad (11)$$

$$+ \beta_{CR,f}CR_t + \gamma_r R_{m,t}^2 + \gamma_v(V_{m,t} - \overline{V}_m)R_{m,t} + \gamma_{m,f}(L_{m,t} - \overline{L}_m)R_{m,t} + \varepsilon_{f,t}$$

where $R_t^2$ is the factor measuring market return timing and is calculated as the squared monthly market excess return, $V_{m,t}$ denotes monthly market volatility and $\overline{V}_m$ is the time series average of the market volatility measure. $V_{m,t}$ is calculated as the standard deviation of daily demeaned market excess returns. Thus a positive and significant timing coefficient $\gamma_r$ indicates positive return timing ability, whereas $\gamma_v$ is negative and significant (i.e. funds decrease market exposure prior to advances in market volatility) if fund managers are able to time volatility.

The results are presented in *Table 14*. The main conclusion is that liquidity timing is clearly separable from the returns and volatility timing factors. Adding factors for returns and volatility timing to the model causes very small changes in the liquidity timing coefficients. The results are essentially unaffected compared to the main analysis in Section 5.1 – fund groups exhibit positive and significant liquidity timing ability, with the only exception being the growth and income fund group when market trading volume is used to proxy for liquidity. As in the main analysis, aggressive growth funds exhibit the strongest liquidity timing ability, followed by growth funds. Growth and income funds' timing ability appears modest when trading volume and turnover are used as liquidity proxies.

Funds show negative volatility timing skill: most of the volatility timing coefficients are positive and significant. This result is inconsistent with Busse (1999), who uses daily returns for a modest sample of 230 US equity funds and documents positive volatility timing ability. CSW (2010) also present evidence of positive volatility timing skill. The evidence on returns timing is mixed: growth and income funds and the aggregate fund sample show slight positive timing ability in volume and turnover tests, but the rest of the coefficients are either significant and negative or statistically insignificant. An extensive body of previous research on timing is in line with the latter observation – mutual funds mostly display negative or insignificant returns timing ability (e.g. Treynor and Mazuy, 1966).

**Table 14**
**Controlling for Returns and Volatility Timing**

Time-series regression results of the liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t$$

$$+ \gamma_r R_{m,t}^2 + \gamma_v(V_{m,t} - \overline{V}_m)R_{m,t} + \gamma_{m,f}(L_{m,t} - \overline{L}_m)R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ excess return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index and $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index. $R_{m,t}^2$ is the squared market excess return measuring for returns timing. $V_{m,t}$ is the month-$t$ market volatility measure and $\overline{V}_m$ is the time-series average of market volatility measures. $L_{m,t}$ is the market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use OLS to estimate the model. Data range from January 1980 to December 2010. Panels A, B and C present results for the Sadka (2006) liquidity measure, trading volume and turnover respectively. $t$-statistics are reported in parentheses, ** and * indicate significance at the 1% and 5% levels respectively.

**Panel A. Sadka Liquidity Measure**

| | **Timing Coefficient** | | |
|---|---|---|---|
| Fund Group | Liquidity | Returns | Volatility |
| Aggressive Growth | 4.469** | -0.177** | 2.834** |
| | (7.69) | (-3.69) | (4.34) |
| Growth | 4.374** | -0.049 | 1.633** |
| | (10.1) | (-1.27) | (2.98) |
| Growth & Income | 3.140** | 0.031 | 1.190** |
| | (9.36) | (1.10) | (3.03) |
| All funds | 1.918** | -0.130** | 6.227** |
| | (19.5) | (-14.5) | (51.2) |

**Panel B. Trading Volume**

| | Timing Coefficient | | |
|---|---|---|---|
| Fund Group | Liquidity | Returns | Volatility |
| Aggressive Growth | 0.531** | -0.257** | 4.081** |
| | (13.5) | (-5.99) | (6.96) |
| Growth | 0.075** | -0.109** | 0.867* |
| | (2.68) | (-4.01) | (2.06) |
| Growth & Income | 0.005 | 0.086** | -0.676* |
| | (0.22) | (3.53) | (-1.96) |
| All funds | 0.043** | 0.031** | 5.686** |
| | (6.09) | (4.37) | (54.6) |

**Panel C. Turnover**

| | Timing Coefficient | | |
|---|---|---|---|
| Fund Group | Liquidity | Returns | Volatility |
| Aggressive Growth | 0.101** | -0.053 | 1.933** |
| | (14.3) | (-1.27) | (3.19) |
| Growth | 0.039** | -0.042 | 0.224 |
| | (7.17) | (-1.47) | (0.53) |
| Growth & Income | 0.016** | 0.101** | -0.979** |
| | (3.65) | (4.18) | (-2.76) |
| All funds | 0.037** | 0.101** | 5.046** |
| | (29.3) | (13.4) | (47.6) |

Altogether the results suggest that funds exhibit positive liquidity timing ability that is unrelated to returns or volatility timing. Results from the main analysis of timing ability remain essentially unchanged. Mutual funds also seem more successful in timing liquidity than timing returns or volatility, even though these three aspects are correlated.

### *5.3.4 Sub-Period Tests*

In the following I test whether the results indicating positive timing ability are robust across time. I divide the fund sample into two sub-samples roughly equal with respect to time: the first sub-period ranges from January 1980 to June 1995, and the second one from July 1995 to December 2010. I then run the liquidity timing regression presented in *Equation (7)* for both sub-samples. *Table 15* presents results for the sub-period tests. Overall, the results suggest that funds' liquidity timing is stronger in the latter time period, reported in Panel B. Interestingly, aggressive growth funds exhibit negative timing ability in the first half of the sample period, but strongly positive timing skill in the latter. For the rest of the funds differences between the two sub-periods are not as striking.

Clearly the observed timing ability is somehow driven by the latter sub-period. Sadka coefficients improve significantly for all fund groups, and aggressive funds improve volume and turnover timing. A natural explanation could lie in developments of the fund market: the latter sub-period probably contains a much larger portion of specialized funds, which have more sophisticated investment strategies. Considering how new the topic of liquidity and its implications for funds management is finance research, it is possible that funds have not actively engaged in this type of market timing until recently.

With the turnover liquidity measure, growth funds and the aggregate fund portfolio exhibit larger positive timing ability in the first sub-period. A decline in observed positive timing skill would be consistent with the rational expectations model of Berk and Green (2004). Their model implies that investors react to observed fund performance, so that outperforming funds receive higher fund flows. Increased fund flows, in turn, make future excess returns more competitive and they are soon wiped out – as a result superior fund performance is short-lived and doesn't show persistence. This could explain why certain fund groups exhibit stronger positive timing ability in the first sub-period.

**Table 15**
**Sub-Period Tests of Liquidity Timing**

Time-series regression results of the liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t$$
$$+ \gamma_{m,f}(L_{m,t} - \overline{L}_m)R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ excess return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. The model is estimated using the Sadka (2006) permanent-variable liquidity measure, trading volume and turnover as the market liquidity measure $L_{m,t}$. I use standard OLS to estimate the model. Data range from January 1980 to December 2010. $t$-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

**Panel A. January 1980 - June 1995**

| | **Liquidity Timing Coefficient $\gamma_{m,f}$** | | |
|---|---|---|---|
| Fund Group | Sadka | Trading Volume | Turnover |
| Aggressive Growth | -11.71** | -0.371 | -0.126 |
| | (-1.98) | (-1.15) | (-0.82) |
| Growth | 1.592*** | 0.048 | 0.150*** |
| | (3.15) | (1.14) | (3.90) |
| Growth & Income | 1.136* | 0.002 | 0.003 |
| | (1.84) | (0.05) | (0.07) |
| All Funds | 0.095 | 0.087*** | 0.136*** |
| | (0.66) | (6.50) | (11.5) |

**Panel B. July 1995 – December 2010**

| | **Liquidity Timing Coefficient $\gamma_{m,f}$** | | |
|---|---|---|---|
| Fund Group | Sadka | Trading Volume | Turnover |
| Aggressive Growth | 4.962*** | 0.498*** | 0.108*** |
| | (8.83) | (12.8) | (15.5) |
| Growth | 4.149*** | 0.012 | 0.032*** |
| | (7.49) | (0.32) | (5.73) |
| Growth & Income | 2.401*** | 0.031 | 0.010** |
| | (6.77) | (1.23) | (2.43) |
| All Funds | 3.733*** | 0.047*** | 0.031*** |
| | (33.9) | (5.69) | (23.6) |

### *5.3.5 Mutual Fund Trading and Market Liquidity*

A valid concern in liquidity timing research is that mutual funds may themselves affect market liquidity and thus give a false appearance of liquidity timing ability. Especially large funds' trading at time *t* could affect aggregate liquidity at time *t+1*. As an example, funds may liquidate their equity holdings simultaneously in one month, which could deteriorate market liquidity in the next month. This would artificially create a positive relationship between a fund's systematic risk and market liquidity.

To test for the effects of fund trading on market liquidity and fund timing ability, I run the liquidity timing test presented in *Equation (7)* on sub-samples of funds sorted by total net assets. The main focus here is on the smallest funds, because their trading is less likely to affect aggregate market liquidity. Specifically, I divide funds into quartiles and deciles based on average fund TNA. The lowest TNA quartile includes funds with TNA less than $20 million, and the lowest decile includes funds with TNA of less than $8.9 million. The highest TNA quartile contains funds with TNA of over $235 million, and the highest decile TNAs of over $716 million.

*Table 16* presents liquidity timing results for the four TNA quartiles and the entire portfolio of funds[14]. Results for the return reversal related Sadka liquidity measure are comforting as the timing coefficients are positive and significant for all size quartiles and both deciles employed. Timing coefficients for the lowest and highest TNA quartiles are 2.10 and 1.94 respectively, with robust *t*-statistics of 8.3 and 14.3. These translate into an approximately 2.2% relative adjustment in fund equity beta for the lowest TNA quartile of funds, and a 2.6% adjustment for the highest TNA quartile, in case of a one-standard-deviation increase in aggregate liquidity. For the lowest decile of funds the liquidity timing coefficient (relative adjustment in beta) stands at 2.38 (2.4%) and for the highest TNA decile 1.67 (2.2%). Results for TNA deciles are reported in *Appendix 1*.

[14] To save space, results for fund TNA decile portfolios are reported in *Appendix 1*.

## Table 16
## Does Fund Trading Affect Liquidity and Timing Results?

Time-series regression results of the seven-factor liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t$$

$$+ \gamma_{m,f}(L_{m,t} - \overline{L}_m)R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ excess return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use OLS to estimate the model. Data range from January 1980 to December 2010. Timing test results are reported for equally weighted portfolios of funds divided into quartiles based on fund TNA. Panels A, B and C report results for the Sadka (2006) permanent-variable liquidity measure, trading volume and turnover, respectively. *t*-statistics are reported in parentheses, ** indicates significance at the 1% level.

**Panel A. Sadka Liquidity Measure**

| Fund TNA Portfolios | $R_m$ | $\gamma_{m,f}$ | Adj. $R^2$ | ΔBeta | ΔBeta% |
|---|---|---|---|---|---|
| 4th Quartile (Largest) | 0.455** | 1.943** | 0.329 | 0.012 | 2.58 % |
| | (327.6) | (14.3) | | | |
| 3rd Quartile | 0.471** | 2.630** | 0.332 | 0.016 | 3.37 % |
| | (273.3) | (15.2) | | | |
| 2nd Quartile | 0.497** | 2.463** | 0.349 | 0.015 | 2.99 % |
| | (249.2) | (12.4) | | | |
| 1st Quartile (Smallest) | 0.569** | 2.104** | 0.363 | 0.013 | 2.24 % |
| | (218.4) | (8.28) | | | |
| All Funds | 0.492** | 2.261** | 0.344 | 0.014 | 2.78 % |
| | (559.2) | (26.1) | | | |

**Panel B. Volume**

| Fund TNA Portfolios | $R_m$ | $\gamma_{m,f}$ | Adj. R2 | ΔBeta | ΔBeta% |
|---|---|---|---|---|---|
| 4th Quartile (Largest) | 0.470** | 0.079** | 0.356 | 0.043 | 9.21 % |
| | (406.3) | (7.09) | | | |
| 3rd Quartile | 0.495** | 0.051** | 0.369 | 0.028 | 5.69 % |
| | (346.1) | (3.69) | | | |
| 2nd Quartile | 0.522** | -0.004 | 0.382 | -0.002 | -0.39 % |
| | (313.7) | (-0.23) | | | |
| 1st Quartile (Smallest) | 0.579** | 0.019 | 0.380 | 0.010 | 1.80 % |
| | (269.5) | (0.92) | | | |
| All Funds | 0.512** | 0.029** | 0.374 | 0.016 | 3.09 % |
| | (703.4) | (4.11) | | | |

**Panel C. Turnover**

| Fund TNA Portfolios | $R_m$ | $\gamma_{m,f}$ | Adj. $R^2$ | ΔBeta | ΔBeta% |
|---|---|---|---|---|---|
| 4th Quartile (Largest) | 0.468** | 0.035** | 0.381 | 0.031 | 6.69 % |
| | (407.4) | (17.4) | | | |
| 3rd Quartile | 0.492** | 0.040** | 0.382 | 0.037 | 7.43 % |
| | (345.4) | (16.9) | | | |
| 2nd Quartile | 0.517** | 0.039** | 0.369 | 0.035 | 6.77 % |
| | (312.2) | (14.3) | | | |
| 1st Quartile (Smallest) | 0.574** | 0.050** | 0.356 | 0.045 | 7.82 % |
| | (267.0) | (14.7) | | | |
| All Funds | 0.512** | 0.029** | 0.374 | 0.026 | 5.11 % |
| | (703.4) | (4.11) | | | |

Results for trading volume and turnover, in contrast, lead to a mixed assessment of the possible relationship between fund trading activity and liquidity timing. Panel B in *Table 16* presents results for tests employing trading volume as the liquidity proxy. Timing coefficients for the smallest and largest TNA quartiles are 0.019 (*t*-statistic 0.92) and 0.079 (*t*-statistic 7.1) respectively. That is, larger funds show a statistically significant adjustment of approximately 9.2% in fund equity exposure (beta), whereas the timing coefficient for small funds is statistically insignificant and only amounts to a 1.8% adjustment market exposure. For the TNA deciles the difference exists as well, although it is not as pronounced: with a one-standard-deviation increase in aggregate liquidity, the smallest decile of funds adjusts equity beta by approximately 5.5%, and this adjustment is significant at the 10% level. The corresponding adjustment is approximately 10.6% and highly significant for the highest TNA decile of funds. The result seems intuitive, considering that large funds can generate a very large fraction of aggregate trading volume. Apparently caution is needed when drawing conclusions about fund managers' skills in timing trading volume.

Panel C in *Table 16* presents results for tests employing turnover as a liquidity proxy. The liquidity timing coefficient for the lowest TNA quartile of funds is approximately 0.050 with a *t*-statistic of 14.7 – this corresponds to a relative adjustment of fund equity beta of approximately 7.8% with a one-standard-deviation increase in market liquidity. The coefficient for the highest TNA quartile is 0.035 with a *t*-statistic of 17.4. This corresponds to an approximately 6.7% increase in fund equity beta in the absence of timing ability. Liquidity timing tests for the lowest and highest TNA deciles tell a similar story, with relative increases in fund beta of 7.9% and 6.2%, respectively. This suggests that the observed positive liquidity timing is not a result of large funds' trading activity. Small funds are not likely to affect market turnover as significantly as larger ones, yet they show ability to adjust market exposure prior to changes in liquidity.

To sum, tests with the Sadka liquidity measure and turnover suggest that the observed positive liquidity timing is not simply due to the fact that large funds' trading may affect market liquidity and create an artificial impression of liquidity timing. With Sadka, the smallest funds show positive and statistically significant timing ability that is almost the same magnitude as timing ability of the largest funds. Turnover tests give further support to this: both the smallest TNA quartile and decile show positive adjustment in the funds' equity exposure prior to changes in aggregate liquidity.

Interestingly, market trading volume tests show contradicting results, with statistically insignificant liquidity timing ability in case of the smallest fund TNA quartile and decile. Larger funds display both economically and statistically significant adjustment in systematic risk with changes in liquidity. Considering that the three liquidity proxies measure different aspects of aggregate liquidity, it seems plausible that the results differ. A natural explanation could be that large funds themselves generate the trading volume used as a liquidity measure, which thereby distorts results of the liquidity timing tests.

### 5.3.6 Liquidity Prediction or Reaction?

As discussed in Section 2.4, one of the features of market liquidity is persistence: serial correlation is a likely feature for liquidity. This could make aggregate liquidity easier to forecast, as the liquidity level in month *t+1* contains information from the prior months. Thus fund managers may "time" liquidity based on past liquidity, which is public information for everybody and therefore does not reflect pure timing skill. Ferson and Schadt (1996) note that controlling for public information in traditional market timing models decreases biases and makes their assessment of fund managers' performance look more favorable. Busse (1999) studies mutual fund managers' ability to time market volatility, and decomposes the level of market volatility into a conditional component and a volatility shock. Cao, Chen, Liang and Lo (2011) use the same approach to test for hedge funds' ability to time market liquidity.

As the Sadka liquidity measure is itself a liquidity shock, it is not suitable for the analysis. Therefore I run the liquidity reaction tests for the two other liquidity measures, volume and turnover. For trading volume, first-order autocorrelation measures up to 0.48 and is statistically significant. For turnover, first-order autocorrelation is even higher at approximately 0.73, which is also significant. Higher order correlations are lower for both liquidity measures and but still significant. With such persistence in market liquidity measures, fund managers could use observed liquidity in month *t* to derive a predictable component of liquidity in month *t+1* and adjust the fund's market exposure accordingly.

In the following I test for the possibility that fund managers simply react to publicly available information on past liquidity instead of actually predicting and timing market liquidity. Specifically, I use a modified liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{0,f,m} R_{m,t} + \sum_{j=1}^{J} f_{j,t} + \gamma_1 \tilde{L}_{m,t} R_{m,t} + \gamma_2 (L_{m,t-1} - \overline{L}_m) R_{m,t} + \varepsilon_{f,t} \tag{12}$$

where $\tilde{L}_{m,t}$ is the monthly liquidity innovation from an AR(1) process[15] and represents the unpredictable component of market liquidity, $L_{m,t-1}$ is the one-month lagged value of the market liquidity measure and $f_{j,t}$ denotes for the Fama-French factors for size, value and momentum as well as the factors for fixed income and credit risk. In this case $L_{m,t-1}$ can be considered the predictable component of aggregate liquidity, and its coefficient $\gamma_2$ measures fund managers' reaction to past liquidity conditions. $\gamma_1$ measures liquidity timing ability; if

[15] I also run the tests with liquidity innovations from an AR(5) process, but the results are essentially unchanged and therefore not reported here.

it's positive and significant, fund managers are able to predict changes in liquidity from information other than past liquidity levels. If fund managers only react to past liquidity, liquidity timing coefficients $\gamma_1$ should be insignificant once the factor for liquidity reaction has been added to the model.

Panel A in *Table 17* lists results for trading volume tests. All coefficients measuring timing ability are positive and significant, with aggressive growth funds exhibiting the strongest timing ability and growth funds following. Coefficients (*t*-statistics) for aggressive growth, growth and growth and income funds are 0.500 (12.7), 0.246 (8.50) and 0.128 (5.50) respectively. The timing coefficient for the portfolio of all funds is approximately 0.159 with a *t*-statistic of 21.8. Besides predicting liquidity, aggressive growth funds also seem to be "timing" past liquidity, i.e. adjusting market exposure based on liquidity in the previous month. The coefficient on liquidity reaction ($\gamma_2$) is 0.356 (*t*-statistic 8.97) for aggressive funds, but negative and significant for all other fund groups.

Panel B presents results for *Equation (12)* performed with turnover as the liquidity measure. The results are very similar to those for the trading volume tests in Panel A. All fund groups show ability to time liquidity: the coefficients on liquidity innovations from an AR(1) process are positive and statistically significant. $\gamma_1$ (*t*-statistics) for the portfolios of aggressive growth, growth, growth and income and all funds are approximately 0.139 (17.4), 0.064 (10.7), 0.029 (6.03) and 0.067 (47.9), respectively. Again, aggressive growth funds appear to exploit information about past liquidity; the coefficient for liquidity reaction is approximately 0.048 and significant at the 1% level. The portfolio of all funds also shows slight positive liquidity reaction.

Altogether, the results from tests combining liquidity timing with controls for liquidity reaction suggest that fund's engage in active liquidity timing that is not related to publicly available information about past liquidity. Liquidity timing coefficients are significant and approximately the same magnitude as in the main analysis (see Section 5.1) for both trading volume and turnover. The results are also quite consistent with earlier tests, showing that aggressive funds are the most able volume and turnover timers, followed by growth funds and growth and income funds. For some reason, the data show perverse liquidity reaction by mutual funds. Aggressive growth funds are the only fund group showing positive and significant liquidity reaction ability.

## Table 17
## Liquidity Prediction Or Liquidity Reaction?

Time-series regression results of the liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{0,f,m} R_{m,t} + \sum_{j=1}^{J} f_{j,t} + \gamma_1 \tilde{L}_{m,t} R_{m,t} + \gamma_2 (L_{m,t-1} - \overline{L}_m) R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ excess return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $f_j$ denotes the month-$t$ Fama-French factors for size, value and momentum strategies ($SMB_t$ , $HML_t$ and $UMD_t$), the month-$t$ return on the Barclays US Aggregate Bond Index ($FI_t$) and the month-$t$ return on the Barclays US High-Yield Corporate Index ($CR_t$). $\tilde{L}_{m,t}$ is the liquidity innovation from an AR(1) process representing the unpredictable component of liquidity based on past liquidity. $L_{m,t-1}$ is the one-month lagged market liquidity level, representing a predictable component of liquidity based on public information. Coefficients $\gamma_1$ and $\gamma_2$ measure liquidity timing and liquidity reaction, respectively. To save space, only these two coefficients are reported. Panel A presents results for trading volume tests and Panel B for turnover tests. I use standard OLS to estimate the model. The data range from January 1980 to December 2010. *t*-statistics are reported in parentheses. ** indicates significance at the 1% level.

**Panel A. Trading Volume**

| Fund Group | Timing ($\gamma_1$) | Reaction ($\gamma_2$) | Nr of obs. | $R^2$ |
|---|---|---|---|---|
| Aggressive Growth | 0.500** | 0.356** | 67 944 | 0.390 |
| | (12.7) | (8.97) | | |
| Growth | 0.246** | -0.290** | 80 171 | 0.654 |
| | (8.50) | (-9.52) | | |
| Growth & Income | 0.128** | -0.215** | 179 100 | 0.400 |
| | (5.50) | (-9.06) | | |
| All funds | 0.159** | -0.152** | 1 744 496 | 0.375 |
| | (21.8) | (-20.3) | | |

**Panel B. Turnover**

| Fund Group | Timing ($\gamma_1$) | Reaction ($\gamma_2$) | Nr of obs. | $R^2$ |
|---|---|---|---|---|
| Aggressive Growth | 0.139** | 0.048** | 67 944 | 0.391 |
| | (17.4) | (6.35) | | |
| Growth | 0.064** | 0.008 | 80 171 | 0.653 |
| | (10.7) | (1.35) | | |
| Growth & Income | 0.029** | -0.014** | 179 100 | 0.399 |
| | (6.03) | (-3.07) | | |
| All funds | 0.067** | 0.016** | 1 744 496 | 0.375 |
| | (47.9) | (12.2) | | |

## 6 Conclusions

This thesis focuses on the liquidity timing ability of actively managed US mutual funds, using a large fund and market data set ranging from January 1980 to December 2010. I use a liquidity timing regression model to estimate whether funds increase (decrease) equity market exposure in anticipation of more (less) liquid markets. I also test for certain cross-sectional differences in mutual funds' liquidity timing ability, and perform several additional tests and robustness checks. The main conclusion is that actively managed funds show positive liquidity timing ability, and that there are cross-sectional differences in timing ability related to fund investment style and certain other fund characteristics. My tests show that aggressive growth funds exhibit the strongest liquidity timing skill, followed by growth funds and growth and income funds. The relative adjustment in average fund beta in case of a one-standard-deviation increase in aggregate liquidity ranges from approximately 2.8% to 7.5%, depending on the liquidity measure used.

My thesis contributes to the so far limited strand of fund liquidity timing research, which has presented mixed results. To my knowledge, Cao, Simin and Wang's (2010) and Winter's (2011) papers are the only published research on the topic thus far. Previous findings on liquidity and asset returns motivate further investigation of funds' liquidity timing ability. Several studies suggest that asset return sensitivity to market liquidity is priced (e.g. Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen; 2005). There is also evidence that liquidity co-moves and predicts future asset returns (e.g. Amihud, 2002; Chordia et al., 2001) and that co-movement in liquidity is higher during large negative market returns (Hameed, Kang and Viswanathan, 2010). These considerations highlight the importance of liquidity in asset management.

I apply three measures of aggregate liquidity that are widely used to estimate market liquidity but haven't been used in previous fund timing studies. The Sadka (2006) permanent-variable liquidity measure is related to return reversals caused by trading and is calculated from intra-day trading data. The two other liquidity measures, trading volume and turnover, measure stock market trading activity related liquidity. Considering how multifaceted the concept of liquidity is, these three liquidity measures give a surprisingly consistent view of mutual funds' timing ability. Although my data sample contains both equity and fixed income funds, I decide to use equity market based liquidity measures. This is motivated by previous research in the pricing of liquidity risk and liquidity commonality: empirical evidence suggests that common factors drive liquidity in both equity and bond markets (see e.g. Chordia, Sarkar and Subrahmanyam, 2005) and that the same equity-based liquidity factors that price systematic liquidity risk in equity returns also price bond returns (Lin, Wang and Wu, 2011).

Perhaps the most explicit way of presenting the results is to estimate relative change in average fund equity beta in case of a one-standard-deviation change in aggregate liquidity. For the aggregate fund portfolio of 21,500 US mutual funds, the Sadka liquidity measure, trading volume and turnover timing tests imply adjustments of 2.8%, 3.1% and 7.5% in fund equity exposure, respectively. These results are all statistically significant and consistent with the findings of Cao, Simin and Wang (2010), who use the Pastor-Stambaugh liquidity measure and find that funds on average increase exposure by approximately 4% with a one-standard-deviation increase in liquidity.

The riskiness of a fund's investment strategy appears to influence how well funds implement liquidity timing. Aggressive growth funds exhibit the strongest liquidity timing skill estimated with all three liquidity measures – relative adjustment in fund beta amounts to approximately 5.7% for the return reversals related Sadka measure, 14% for turnover and 52% for volume liquidity timing tests. Aggressive funds are followed by growth funds, for which estimates of adjustment in systematic risk range from 3% to 4%. Growth and income funds show significant timing ability with the Sadka liquidity measure and turnover: adjustment in average fund beta is approximately 3.0% and 1.7%, respectively. Again, these results are consistent with those previously reported by Cao, Simin and Wang (2010). So why would funds with riskier investment strategies consistently outperform other funds in liquidity timing? One explanation could be fund holdings: Chen, Hong, Huang and Kubik (2004) show that aggressive funds invest more heavily towards small-cap stocks, which are usually less liquid. It's conceivable that funds holding less liquid assets are more skilled in timing aggregate liquidity.

I also test for cross-sectional differences in liquidity timing ability related to fund characteristics. My results indicate that fund fees, normalized flows and the volatility of flows are positively related to timing ability, whereas turnover has a negative relationship with timing skill and fund age appears insignificant. Evidence on fund size is mixed. The observed relationship with fees is intuitively appealing: successful liquidity timers provide a hedge and are able to charge extra for this service. There is also some evidence of a positive relationship between timing ability and fund flows, but it remains uncertain whether investors recognize fund managers' timing skill and allocate funds accordingly. The observed positive relationship between fund flow volatility and timing ability is consistent with the evidence that aggressive growth funds exhibit the highest flow volatility. On the other hand, volatile fund flows could impede implementation of fund managers' investment strategies, including liquidity timing. Finally, my data shows some evidence that successful liquidity timing funds trade less actively: turnover is negatively related to Sadka liquidity timing ability. Apparently, the objective of adjusting market exposure with respect to liquidity does not require more trading compared to non-liquidity-timing funds.

A possible concern is that the results are simply due to a passive liquidity timing effect, and not active timing skill by fund managers. This could happen, for example, if the systematic risk of fund holdings changes in time. I run the liquidity timing tests for a sample of US equity index funds and find that timing coefficients are statistically significant but economically negligible in magnitude, unlike for actively managed funds. Thus the observed liquidity timing appears to be the result of active portfolio management. I also test for the possibility of returns timing or market volatility timing manifesting itself in liquidity timing coefficients. Liquidity timing is clearly separable and remains essentially unchanged after controlling for returns and volatility timing. The timing results are not driven by an omitted liquidity risk factor in fund returns, either.

Sub-period tests reveal that liquidity timing ability is strongly connected to the latter half of the sample period (1995-2010). The majority of funds exhibit insignificant or negative timing skill in the earlier time period, whereas the latter sub-period exposes strong positive timing skill. Considering how recent the topic of fund liquidity timing is in finance literature, it could be that fund managers have also started to include liquidity concerns into portfolio management more recently. Furthermore, the mutual fund market has developed significantly during the latter time period, with funds employing more and more advanced investment strategies. This would be a natural explanation to the observed differences between the two sub-periods. On the other hand, the portfolio of all funds shows declining volume and turnover timing ability, which would be consistent with the idea that investor's chase for the best performing funds wipes out excess returns and outperformance is short-lived (see e.g. Berk and Green, 2004).

In addition to the latter half of the sample time period standing out, liquidity timing seems to be especially important during times of market turmoil and declining liquidity. When I exclude the market crash of 1987 and the 2008 liquidity squeeze related to the financial crisis from the analysis, inference of liquidity timing ability becomes significantly weaker. The results suggest that active liquidity management is most important during periods of declining market liquidity. Fund managers seem to execute significant adjustments in market exposure prior to major liquidity events, but neglect this aspect of portfolio management during "normal" market conditions.

As mutual funds generate a large amount of trading activity themselves, a potential concern is that large funds' trading affects market liquidity and creates an artificial appearance of liquidity timing. In my sample, funds belonging to the largest TNA quartile and decile have total net assets greater than $235 million and $716 million respectively. As a result they're capable of affecting liquidity, especially if trading needs coincide. I test for differences in liquidity timing between fund TNA quartiles and deciles. The results suggest that the observed liquidity timing ability isn't simply due to funds' own trading affecting market liquidity, and this holds for all three liquidity measures. I also use an alternative timing model specification to test for the possibility that funds only react to public information on past liquidity, as opposed to actually predicting future liquidity conditions. Again, the empirical results suggest that fund managers anticipate changes in aggregate liquidity and adjust the fund's market exposure based on that. Aggressive funds appear to be the only fund portfolio showing significant positive liquidity reaction. This is somewhat puzzling, as it would seem natural that funds take advantage of the information included in past liquidity levels.

My study builds on the previously documented evidence on mutual fund's market timing ability. Whereas extensive research implies insignificant or negative market returns timing and positive market volatility hedging skill, the empirical evidence on funds' liquidity timing is still relatively scarce. Both my study and the evidence presented by Cao, Simin and Wang (2010) imply that mutual funds do engage in liquidity timing, are somewhat successful at it, and that there are cross-sectional differences in funds' timing skill. Liquidity timing appears to be a rather recent phenomenon in fund portfolio management. The results also indicate that mutual fund managers do not normally engage in active liquidity management, but managing market exposure becomes relevant during times of significantly decreasing liquidity.

My thesis and the existing literature in funds' liquidity timing leave room for further research on the topic. For instance, I do not address the effect of the observed liquidity timing ability on mutual fund returns. Cao, Simin and Wang (2010) and Cao, Chen, Liang and Lo (2011) use alternative liquidity measures and find that successful liquidity timing mutual funds and hedge funds outperform unsuccessful funds. Yet further evidence is needed on whether timing skill translates into higher returns. As my results suggest the observed timing skill is heavily related to periods of extraordinary liquidity, it would be interesting to study more closely the role of liquidity in fund management in different market conditions. Naturally, the research topic should also be extended to mutual funds outside of the US, as well as examining the cross-sectional differences between funds with more extensive and refined fund characteristics data.

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# 8 Appendices

## Appendix 1
## Does Fund Trading Affect Liquidity? Fund TNA Deciles

Time-series regression results of the seven-factor liquidity timing model:

$$R_{f,t} = \alpha_f + \beta_{f,m,0}R_{m,t} + \beta_{SMB,f}SMB_t + \beta_{HML,f}HML_t + \beta_{UMD,f}UMD_t + \beta_{FI,f}FI_t + \beta_{CR,f}CR_t$$

$$+ \gamma_{m,f}(L_{m,t} - \overline{L}_m)R_{m,t} + \varepsilon_{f,t}$$

where $R_{f,t}$ denotes the fund $f$ excess return in month $t$, $R_{m,t}$ is the month-$t$ return on the CRSP value-weighted market portfolio in excess of the one-month T-Bill rate, $SMB_t$ , $HML_t$ and $UMD_t$ denote the month-$t$ Fama-French factors for size, value and momentum strategies respectively, $FI_t$ is the month-$t$ return on the Barclays US Aggregate Bond Index, $CR_t$ is the month-$t$ return on the Barclays US High-Yield Corporate Index, $L_{m,t}$ is the market liquidity measure for month-$t$ and $\overline{L}_m$ is the time-series average of market liquidity measures. I use OLS to estimate the model. Data range from January 1980 to December 2010. Timing test results are reported for equally weighted portfolios of funds divided into quartiles based on fund TNA. Panels A, B and C report results for the Sadka (2006) permanent-variable liquidity measure, trading volume and turnover, respectively. $t$-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

**Panel A. Sadka Liquidity Measure**

| TNA Portfolio | $R_m$ | $\gamma_{m,f}$ | Adj. $R^2$ | ΔBeta | ΔBeta% |
|---|---|---|---|---|---|
| 10th Decile (Largest) | 0.459*** | 1.670*** | 0.363 | 0.010 | 2.20 % |
| | (237.7) | (8.90) | | | |
| 1st Decile (Smallest) | 0.605*** | 2.384*** | 0.349 | 0.014 | 2.38 % |
| | (142.9) | (5.80) | | | |

**Panel B. Trading Volume**

| TNA Portfolio | $R_m$ | $\gamma_{m,f}$ | Adj. $R^2$ | ΔBeta | ΔBeta% |
|---|---|---|---|---|---|
| 10th Decile (Largest) | 0.608*** | 0.061* | 0.414 | 0.033 | 5.47 % |
| | (173.8) | (1.82) | | | |
| 1st Decile (Smallest) | 0.470*** | 0.091*** | 0.370 | 0.050 | 10.63 % |
| | (291.9) | (5.93) | | | |

**Panel C. Turnover**

| TNA Portfolio | $R_m$ | $\gamma_{m,f}$ | Adj. $R^2$ | ΔBeta | ΔBeta% |
|---|---|---|---|---|---|
| 10th Decile (Largest) | 0.603*** | 0.052*** | 0.414 | 0.047 | 7.87% |
| | (172.1) | (9.68) | | | |
| 1st Decile (Smallest) | 0.468*** | 0.032*** | 0.370 | 0.029 | 6.15% |
| | (293.4) | (11.3) | | | |