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Acknowledgments

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Abstract

In Chapter 1 I investigate the economic importance of correlation in mutual fund flows for funds with overlapping portfolio positions. I illustrate theoretically that commonality in trading by funds due to flow correlation influences the optimal portfolio. Furthermore, I show that the expected return from an asset for a specific agent is conditional on correlation of this particular asset holder's flows with his peers. Finally, I derive a theoretical upper bound of optimal flow correlation and hypothesize the existence of at least one optimal equilibrium outcome for any combination of pairwise fund flow correlations. Empirically, I introduce a measure of portfolio adjusted flow correlation and find that comovement in flows can significantly deteriorate fund performance in the long-run, by about 1.4% annually between peer funds with high and low correlation, adjusted for style. Finally, I find that around one third of US mutual funds holds non-optimal portfolios as far as dynamic liquidity from correlated trading patterns is concerned.

The research in Chapter 2 presents evidence for the existence of differences in asset beta risk in the liquidity cross-section of stocks. I argue that because of differences in liquidity (or trading cost), most trading activity is concentrated on the subset of liquid assets. In the presence of systematic wealth shocks this leads to an increase in beta risk for the liquid asset class beyond their true level of risk from the underlying dividend process with regard to the market risk factor. Vice-versa, the risk of illiquid assets becomes understated. Moreover, it is argued that a reduction of trading cost in the cross-section will reduce such differences and lead to a convergence of risk factor estimates towards the true value of underlying risk. Empirical evidence using data surrounding the tick-reduction event at the New York Stock Exchange is supporting this hypothesis. I find that beta estimates for liquid assets exceed their illiquid peers, while the difference in beta between the groups is significantly reduced after the ex-

ogenous trading cost reduction due to the tick-change event.

In Chapter 3 I investigate asset liquidity surrounding fire-sale events by mutual funds. I develop revised method for identifying liquidity-driven sales. I find empirical evidence of both front running and liquidity provision surrounding liquidity-driven fire-sale events. Applying my identification method for sample selection I find significantly faster rates of return reversal compared to previous literature. Moreover, I show that asset liquidity measures return to their intrinsic values very shorty after a fire-sale. Finally, I show that a trading strategy of liquidity provision by outsiders provides economically significant returns.

Keywords: Delegated Investment Management, Liquidity, Asset Pricing, Portfolio Choice, Fire Sales.

Resumen

En el Capítulo 1 investigo la importancia económica de la correlación entre los flujos de fondos relativos a fondos de inversión con carteras similares. Demuestro de forma teórica que la similitud entre las estrategias de trading de distintos fondos de inversión causadas por la alta correlación entre sus flujos de fondos influye en las decisiones óptimas sobre carteras de inversión. De forma adicional, demuestro que el retorno esperado de los activos está condicionado a la correlación de las corrientes de fondos con sus competidores. Finalmente, derivo el límite superior teórico de correlación y presento la hipótesis de existencia de una cartera óptima para cada posible matriz de covarianzas. Introduzco una medida de correlación de flujos de fondos, ajustada por la cartera de inversión. Empíricamente, encuentro una caída del rendimiento a largo plazo de un 1.4% anualmente entre fondos de inversión con estilo similar de inversión. Además, demuestro que un tercio de los fondos de inversión en los EEUU adoptan carteras de inversión subóptimas con respeto a la dinámica de la liquidez derivada de la cercanía en sus estrategias de inversión.

En el Capítulo 2 presento evidencia empírica de que existen diferencias en el riesgo beta de los activos en la sección cruzada de la liquidez de las acciones. Las diferencias de liquidez o de costes de transacción hacen que los agentes centren su actividad de trading sobre la clase de los activos más líquidos. Cuando existe el riesgo de shocks a la riqueza sistémicos, esto genera un incremento en el riesgo beta para la clase de los activos más líquidos en exceso del valor real del riesgo que se deriva de sus dividendos con relación al factor de riesgo de mercado. Y vice-versa, el riesgo de los activos ilíquidos se subestima. Una reducción uniforme en costes de transacción puede reducir dicha diferencia entre las betas. Demuestro de forma empírica que esto es así, utilizando datos sobre precios de activos durante el período de cambio de la forma de contabilizar los precios que ocurrió en el New York Stock Exchange. Demuestro que la reducción de costes puede

reducir la diferencia en la beta entre activos líquidos y ilíquidos.

En el Capítulo 3 estudio cambios en la liquidez de los activos durante ventas masivas por parte de fondos de inversión. Introduzco una innovación en la metodología de identificación de ventas por razones de liquidez frente a ventas por razones de valoración. Encuentro evidencia empírica de pre-venta de activos y provisión de liquidez durante de las ventas masivas por razones de liquidez. Utilizando mi método de identificación de ventas por razones de liquidez encuentro reversión de rendimientos negativos significativamente más rápida que la que habían encontrado estudios anteriores. Demuestro también que las medidas de liquidez de los activos vuelven a sus valores intrínsecos inmediatamente después de las liquidaciones. Finalmente, demuestro que una estrategia de provisión de liquidez genera rendimientos positivos económicamente significativos.

Palabras clave: Fondos de inversión, Liquidez, Valorización de Activos, Selección de Carteras, Ventas por Falta de Liquidez.

Foreword

This thesis is about the effects of stochastic liquidity needs on financial markets. Throughout this work I consider liquidity as the immediate need (or availability) of funds at a particular point in time. This concept of liquidity is typically referred to as "funding liquidity" in academic literature and describes the availability or need of cash on the balance sheet of economic agents. The complementary concept of "asset liquidity" describes the ease of selling or buying of a financial asset at a particular moment in time, which in turn is determined largely by the amount of funds available to interested buyer/sellers. Variations in liquidity ultimately lead to transactions of financial assets, as agents with excess funds will invest such, while agents with a need for cash are forced to sell some of their assets. The level of immediacy required by the liquidity needs of agents translates into a cost for the buyer or seller at the time of a transaction. So, for example, an agent who needs to immediately sell a large volume of a financial asset which is not traded frequently, is likely to have to sell these holdings at a considerable discount. On the other hand, if the same agent did not have such an immediate need for cash and can delay some portion of the sale, the cost incurred would likely be lower. Hence, liquidity driven sales can temporarily move the price of an asset away from its fundamental value, therefore imposing a "liquidity cost" that is proportional to the size and immediacy of the liquidity shock.

On the other hand, transaction cost of trading an asset must be considered. Two types of transaction cost need to be distinguished. First, there may exist a fixed cost when trading an asset, such as a handling fee for example. Assets with high fixed transaction cost are considered illiquid assets, yet this relationship should be seen as a second order effect. High fixed costs reduce net per-period returns more severely the shorter the asset is held, which makes frequent trading of such an asset less attractive. This reduces the amount of interested buyers/sellers at a given point in time, and therefore leads to a low level of liquidity. A second type of transaction cost is the spread between the bid and ask price required by the market maker. Contrary to the first type, this cost is directly proportional to the liquidity of an asset, since the market-maker demands a higher spread to deal an illiquid asset in order to be compensated for inventory risk.

"Liquidity risk" refers to the stochastic properties of agents' liquidity shocks (or wealth shocks). Random liquidity needs lead to random trading activity of agents. For example, a risk-free asset with high fixed trading cost yields stochastic net period returns once an agent's trading horizon becomes stochastic. So, such an asset would be preferred by agents with lower levels of liquidity risk, such agents in turn would demand a premium for holding the asset. As agents are risk averse, such a premium exceeds the discounted value of trading cost in equilibrium.

In most of the standard liquidity literature, agents are assumed to have stochastically independent liquidity shocks with either heterogeneous or identically distributions. This way of modeling serves well to explain the existence of liquidity premia in the market, but cannot explain variations in aggregate liquidity since independently distributed shocks cancel out at an aggregate level. In this thesis I assume that liquidity needs or funding shocks are correlated across agents. While such correlation can arise from various sources such as dependence on some common systematic factor, I do not explicitly investigate the source or dynamics of such correlation in this work, but rather concentrate on the effect of such correlation.

In Chapter 1 of this thesis I present a portfolio choice model for a population of mutual fund investors with clustered correlation of liquidity shocks. Empirically, such clustered correlation in liquidity is observed in the mutual fund industry. The idea is that when allowing for heterogeneous levels of correlation across a population, an agents' incurred liquidity cost becomes conditional on his trading needs with respect to the size and direction of contemporaneous liquidity-driven trades of the remainder of the population. I incorporate expected simultaneous trading between agents into a portfolio choice model, where the optimal portfolio minimizes incurred liquidity cost for each agent. In equilibrium this leads to diversification away from the portfolio held by other agents within the respective correlation cluster up to a point where liquidity cost from simultaneous trading gets spread evenly across the population. I introduce an empirical measure representing the exposure of mutual funds to excessive liquidity cost from portfolio positions that are not sufficiently different from holdings of other agents within the same flow-correlation cluster.

In the second chapter I investigate the effect of systematically correlated trading within a population of agents on the beta risk factors of assets in the liquidity cross-section. While, as long as liquidity needs cancel out between agents at the aggregate level, liquidity driven trading does not have an impact on the systematic price-risk of assets. Once systematic correlation is introduced, trades no longer cancel out in the aggregate. For homogeneous trading cost, an increase in systematic aggregate liquidity risk increases systematic price risk evenly across assets, making the return on the market portfolio more volatile. But, as discussed earlier, assets with lower levels of trading cost are better suited to be traded for liquidity reasons, hence liquidity driven trading is concentrated on the class of liquid assets and their systematic price risk therefore increases disproportionally. As trading cost is asymmetric in the cross-section, illiquid assets are not affected as much by the increase in systematic risk. I show that when measuring systematic price risk using the Capital Asset Pricing Model, the beta risk coefficient of liquid assets is above the beta of illiquid assets. Furthermore, I show that this difference is reduced, for a reduction in trading cost.

In Chapter 3 I analyze the behavior of liquidity characteristics of assets around fire sales by mutual funds. Such large liquidity-driven sales result in significant negative price pressure, leading to a temporary drop in the asset price around the sale event. I argue that after the sale is completed the level of asset liquidity should be similar to the level before the sale and the price of the asset should return to its intrinsic value. Yet, in the empirical literature investigating fire sales, observed return reversals on average last over 18 months. Such long return reversals could be caused by a permanent drop in asset liquidity after the fire sale, as agents might consider a liquid pre-sale asset to be less liquid after the sale. Such behavior would result in the asset actually being less liquid, because, if it is traded less frequently after the sale, its bid-ask spread would increase, which increases the assets' transaction cost. In order to answer this question, I compare the behavior of asset-liquidity characteristics for large liquidity and value-driven sales by mutual funds. Additionally, I look for evidence of liquidity provision and measure the profitability of such a liquidity provision strategy after fire-sales.

In general, the aim of this thesis is to contribute to the understanding of the effects created by systematic liquidity needs within a population of investors and to derive strategies of optimal liquidity provision.

Contents

1 The Cost of Funding Flow Correlation

1.1 Introduction

In this chapter I investigate how correlation between funding flows (or liquidity shocks) of investors that hold overlapping portfolios can destroy wealth. Correlated funding flows lead to commonality in trading by investors, which can create significant price pressure if this trading is concentrated on the same set of assets. Additionally, as such price pressure can be positive or negative it makes investors incur trading cost when buying as well when as selling assets. In this study I focus on trading by mutual funds, since, by construction, they must make liquidity driven trades matching their capital in- and outflows. Moreover, mutual funds typically specialize in trading particular portfolios (such as industry specific stocks for example) and therefore are inclined to hold overlapping portfolios with peer funds. Finally, mutual fund flows are highly correlated between funds. Potential losses for funds from simultaneous trading of overlapping portfolios are therefore high. In order to quantify the risk of incurring such losses I introduce a measure of portfolio-adjusted funding-flow correlation (PFC) and argue that flow correlation should be considered by fund managers in their portfolio choice. I show empirically that if flow-induced trading is contemporaneously positively correlated with cumulative flow-induced trading (and therefore price pressure) of a fund's portfolio, this leads to destruction of fund investors' wealth.

In particular, this paper addresses the following four questions: Why and how should flow correlation (or liquidity driven trading patterns) be a determinant in a portfolio choice problem? Can fund-managers actively influence flow correlation when choosing their portfolios or are they constrained by the actions of fund-investors? What is the impact on mutual fund performance, and is it economically significant? What proportion of funds select their portfolios optimally with regard to flow correlation?

The standard assumptions in financial economics are that agents have either independent and identically distributed (i.i.d.) trading/liquidity needs or that they are not liquidity constrained at all and trade at their own discretion. Either assumption means that, trading patterns are not correlated between agents and can be completely ignored when setting up the portfolio choice problem. In this paper I argue that, once systematic liquidity needs - or correlation in liquidity needs between agents - is introduced, optimal portfolio weights become conditional on the contemporaneous trading needs of an agent with respect to others. Systematic liquidity shocks can create systematic up- and downward price pressure on certain assets, so an agent whose liquidity needs are positively correlated with such systematic shock-induced price movements will have lower expected utility from holding this particular asset compared to an agent whose trading needs are not correlated with the systematic shock which affects the asset price.

In this study I investigate the case of mutual funds with correlated funding flows. It has been shown that capital flows in and out of mutual funds and the resulting flow-induced trading can create significant price pressure on individual stocks and the market portfolio[1]. Mutual fund flows are not necessarily correlated with the fundamentals of the assets held by the fund, though it has been shown empirically that mutual fund flows are correlated with lagged returns[2]. The correlation examined here is between mutual fund flows and the cumulative price pressure in their portfolio due to flow-induced trading by peers. While the effect of price pressure from flow-induced trading on the perfor-

[1]See Coval and Stafford (2007), Ben-Rephael, Kandel and Wohl (2011), Edelen and Warner (2001), etc.

[2]See for example Sirri and Tufano (1998)

mance of assets has been well documented in previous studies[3], I mainly investigate the effect of correlated trading on the performance of the fund itself, not on the asset price. Basically, a fund with positively correlated trading needs with his peers systematically sells too cheap and buys too high[4]. The study most closely related to this chapter is Lou (2010) who calculates a measure of expected flow induced price pressure of fund portfolios, but does not account for the trading dynamics of funds[5]. The PFC measure I introduce here expands the idea of flow induced price pressure by defining expected costs conditional on the contemporaneous trading needs between peers.

My results can be summarized as follows. In the theoretical part of this work, I first illustrate that correlation between mutual fund flows and aggregate value weighted portfolio flows becomes an important variable in choosing the optimal portfolio. I derive this result by formally describing the maximization problem of mutual funds when faced with liquidity driven transaction cost. I further demonstrate that a systematic component in the flows of holders of an asset will decrease the asset price and increase unconditional expected returns. Finally, I derive an upper bound of optimal portfolio (or asset) flow correlation conditional on the fund. Empirically, I estimate the determinants of flow correlation in fund portfolios and find that correlation is higher for funds with high past excess returns and high loads on risk factors. Moreover, correlation increases with portfolio concentration and for less liquid portfolios. Next, I find significant evidence that flow correlation decreases fund excess returns in the long run, when controlling for fund style. I find that high-correlation funds underperform similar low-correlation funds on average by

[3]For example: Coval and Stafford (2007), Frazzini and Lamont (2008) or Koch, Ruenzi and Starks (2009)

[4]Greene and Hodges (2001) show that active trading of open-ended funds has a meaningful negative economic impact on the returns of passive, non-trading shareholders. Here, I argue that once considering flow correlation such a dilution effect on long horizon fund investors may be exacerbated.

[5]The paper by Lou (2010) is discussed in detail in Section 1.2.

1.4% annually. Finally, I show empirically that around one third of funds holds non-optimal portfolios with excess flow correlation.

The rest of the chapter is structured as follows. In Section 1.2 I describe the contribution of this paper to existing literature. Section 1.3 explains the theoretical background, while Section 1.4 outlines the sample selection process. Section 1.5 describes the construction and properties of the flow correlation measure, Section 1.6 outlines the empirical results and Section 1.7 concludes.

1.2 Contribution to existing literature

This work is related to three distinct strands of literature, in particular, the effect of mutual fund flows on assets, mutual fund performance and optimal deviation in portfolio choice. Below, some of the most closely related papers are described in context with the contribution of this chapter. Nevertheless, as these are broad categories of research I do neither attempt to list nor review the cross-section of available literature, but merely mention a few representative and relevant examples.

The first strand of literature investigates the impact of (extreme) mutual fund flows on asset prices and portfolios as well as asset liquidity. In particular this study relates to the "Asset Fire Sales" paper by Coval and Stafford (2007) and Frazzini and Lamont (2008) with their later article "dumb money" as well as Koch et al. (2009) and Anton and Polk (2012). Coval and Stafford (2007) show that large forced changes in mutual fund positions due to outflows creates price pressure. Their empirical results illustrate that stocks, which are held by mutual funds with extreme outflows, exhibit large cumulative negative returns even prior to the outflow, with prices returning to their fundamental value after the outflow event. Coval and Stafford argue that investors pulling their moneys out of mutual funds cause mutual fund managers to sell assets at fire sale prices. Asset prices later recover and the mutual fund forgoes this positive return. As mentioned above, Frazzini and Lamont (2008) argue that mutual fund investors make bad decisions by investing into segments with high past returns, therefore driving up the current price over its fair value. Such liquidity driven excess returns are subsequently destroyed when prices return to the fundamental level and investors begin to withdraw their moneys. The "dumb money" argument is that it is optimal to invest against the general flow of funds. I relate to this argument by showing that mutual fund managers should consider correlation with peers' funds trading when selecting their portfolio, hence avoiding buying overpriced assets alongside everyone else. Koch et al. (2009) document that commonality in liquidity of investors with similar holdings and trading patterns cause commonality in asset liquidity and use mutual funds flows to proxy for investors' liquidity needs. Similarly, Anton and Polk (2012) show that common ownership by mutual funds causes excess co-movement in asset returns. They explain this as a result of commonality in liquidity due to flows, but instead of using flows they look at shared ownership. I add to these papers by arguing that fund managers should be able to outperform their peers by adjusting portfolios for flow correlation. I estimate that commonality in liquidity of investors with similar holdings and trading patterns cause commonality in asset liquidity and use mutual funds flows to proxy trading patterns. Furthermore, this work highlights the relationship between commonality in flow driven funding liquidity and asset prices as well as fund returns.

In contrast to the first strand of literature, which investigates the effect of flows on assets, the second line of related research concerns mutual fund performance, as does this work. The most closely related paper by Lou (2010) first investigates the relationship between mutual fund flows and demand shocks in individual stocks and shows that mutual fund flows can help to explain persistence in mutual fund performance, the "smart money" effect and stock price momentum. Lou reasons that the price pressure from inflows leads to future positive returns, while flow driven liquidations lead to future underperformance, which causes fund performance persistence, momentum and "smart money". His empirical study shows that systematic funding flows have a significant impact on asset prices, similar to Coval and Stafford (2007). He introduces a measure of expected flow induced price pressure (FIPP) and shows that it has predictive power on expected asset returns and expected fund performance. Moreover, it is shown that the expected fund performance can be calculated from the expected FIPP of its portfolio. It is shown that if sorting funds by the FIPP of their portfolios, the top decile outperforms the bottom decile by 4.8% in the first year, while underperforming in the second and third year, which is evidence for a full price reversal. The analysis I present here goes a step further, since I additionally take the dynamic relationship between flows into account and determine the expected cost of liquidity-induced trading conditional on the fund's flow pattern by calculating the covariance between the fund's flow and the aggregate flow of funds holding an overlapping position. The FIPP measure of Lou (2010) shows the impact of other funds' flows on the expected return of the portfolio, but if the fund itself does not have to liquidate jointly with others it will continue to hold a - now undervalued - portfolio with a higher expected future return and will not realize losses from liquidation unless it is forced to liquidate. In the long run such a fund would outperform his peers contrary to what FIPP might predict in this case. Without knowing the dynamic relationship of contemporaneous trading it is difficult to see if a fund that holds a certain portfolio with large FIPP acts as a liquidity provider and buys an undervalued asset when everyone else has to sell, or if it is also forced to sell at a low price. The time and direction of trades in relation to flow-induced mispricing (where price does not reflect the fundamental value of the security) therefore should be a key performance parameter. Additional related fund performance literature includes the ”Smart Money Effect” documented by Gruber (1996) and Zheng (1999) who indicate that funds receiving flows subsequently outperform in the short run. They estimate a significant effect especially for smaller funds. Similar to Lou (2010), I argue that such short run outperformance may be caused by simultaneous trading of overlapping portfolios and that such excess returns are destroyed by increased liquidation costs in the long-run.

The third branch of literature concerns portfolio choice where agents deviate from their peers. The empirical study by Gupta-Mukherjee (2008) provides evidence that active fund managers who deviate from their peer group underperform subsequently in relation to their peers. The reason for such underperformance is not explained. Even though she argues that theoretically fund managers should deviate from their peers to avoid losses from herding (liquidity), she does not control for correlation in fund flows. I make a similar argument but propose to use portfolio adjusted flow correlation as a performance measure instead of trying to empirically define peer-groups in the asset space. The underperformance found in her study might be a investment horizon issue, as I show that funds that deviate from others outperform in the long run. Wagner (2008) shows theoretically that the risk of facing joint liquidation gives investors an incentive to ex-ante choose idiosyncratic portfolios weights, hence reducing the probability of joint liquidation. In his work liquidation is driven by the (under-) performance of the portfolio, whereas I consider liquidity shocks (and hence trading patterns) to be exogenous. In his work he provides a well-defined theoretical model, which shows that deviation from peers becomes the optimal choice once liquidity needs become correlated. I propose that there should exist an optimal level of deviation, which takes the tradeoff between valuation and liquidity into account. Without assuming any explicit causal structure of funds’ flows it is intuitive that winning funds with skilled managers attract inflows, while loosing funds exhibit outflows. This complicates a manager's portfolio choice somewhat, as a fund cannot simultaneously hold the same "winning" portfolio and have uncorrelated flows with the other holders of the same portfolio. Therefore, similar to Wagner's result, I argue that there must exist an optimal level of deviation that maximizes return while minimizing expected cost from liquidity induced trading.

The main contribution of this chapter to existing literature is to show that contemporaneously correlated trading flows and especially portfolio-adjusted funding-flow correlation (PFC) are important parameters in portfolio choice and that they have economic significance in mutual fund performance. Furthermore, I assess to which extent mutual fund managers take PFC into account and if the mutual fund market is competitive once flow correlation is considered, i.e. if flow correlation is a variable from which mutual fund returns can be predicted.

1.3 Theoretical Motivation

A simple example

To illustrate how systematic wealth shocks can influence portfolio choice with a simple example, let us assume a worker who receives the majority of his wealth as labor income from a particular firm and his income is at least partially stochastically linked to the firms performance. The worker now wants to invest his wealth. I argue that for this particular worker, an investment into shares of the employer firm is a relatively bad investment decision[6]. When buying shares of the firm, the worker's investment returns are automatically positively correlated with his income stream. This means, during good times (when the firm does well), he is likely to receive an extra bonus or a salary raise, while simultaneously getting high returns from his stock investment. Whereas, during

[6]Assuming the worker has no insider information.

bad times he is likely to earn less or even loose his job, while his investment also yields low returns. On the other hand, an agent who has an i.i.d. income stream in relation to the performance of the firm will consider the firms stock a relatively better investment in comparison. Basically, the worker's set of stochastic discount factors are partially defined by his stochastic income stream. Hence, for low-income states of nature his marginal utility of wealth is greater, and so is the respective stochastic discount factor. Therefore, correlation between his set of stochastic discount factors and the payoff of the firm's stock is lower compared to an agent with i.i.d wealth. Such lower correlation leads to a lower price this particular worker is willing to pay for the stock. Additionally, the worker is more likely to be forced to liquidate his stock holdings in the bad state, at a low price, while he may invest excess cash in the good state, at a high price, which reduces his expected realized return on the asset. This simple example illustrates that correlation between income, or liquidity, with asset payoffs matters when choosing an investment portfolio.

But, asset returns are not only driven by fundamentals, also liquidity or non-information based trading moves the price of an asset. So, when there is a systematic component in the wealth shocks of constrained agents who trade a particular asset in order to satisfy their liquidity needs, they will cumulatively exert price pressure on the asset due to simultaneous trading. Hence, an agent whose wealth shocks are correlated with the cumulative price pressure from liquidity trading (and therefore are correlated with the wealth shocks of the other holders of the asset) faces a similar problem than the worker described in the example above, even with shocks being completely independent from asset fundamentals[7]. The portfolio choice problem described below formalizes this problem.

[7] Assuming there is no correlation between the particular stock's fundamental value and the agent's wealth, as opposed to the case of the worker.

Portfolio Choice Problem of Mutual Funds with Flow Correlation and Trading Cost

Let there exist I funds (agents)[8] $i = 1 \dots I$ that invest in portfolios of assets $n = 1 \dots N$ with $\omega_{i,n,t}$ portfolio weights. Each fund is subject to exogenous cash inflows and withdrawals (liquidity shocks) by its investors at the end of each period. Let $Flow_{i,t}$ represent inflows (withdrawals for values <0) into (from) fund i at time t. For simplicity let us assume future fund flows to be unexpected flows[9], so $E^t[Flow_{i,t+1}] = 0 \ \forall i$. Moreover, I assume that flows have stochastic variance $E[\sigma_{Flow}] = constant$, $Var[\sigma_{Flow}] > 0$. Finally, let us assume flows to be uncorrelated with fundamental asset returns. The stochastic variance term is used to model uncertainty about fluctuations in liquidity[10] [11].

Since funds must be seen as conduits - they do not own or hold a large amount in cash, but buy and sell assets with their investors' capital - an inflow or outflow of capital has an effect on their portfolio. In case of an outflow - investors taking money out of the fund - a portion of the fund's portfolio must be sold. When a fund receives an inflow of capital it has to invest this money and

[8] Assuming a sufficiently large I so individual funds can be considered marginal price takers.

[9] Empirically, mutual fund flows exhibit high first-order autocorrelation and correlation with the fund's lagged performance, which makes it possible to predict flows at least partially. However, a large part of mutual fund flows remains unpredictable. Arguably, the more interesting part of flows are unexpected flows as far as liquidity is concerned. In any case, it should be considered that funds are not able to react ex-ante even to expected flows, since they i.e. cannot short sell or borrow. I therefore perform the empirical analysis in this paper using total net flows and not just unexpected flows, while, for simplicity, assuming flows to be unexpected in this theoretical section.

[10] In this dynamic setup the absolute level of liquidity does not matter, the expectation of volatility in aggregate liquidity is important for expected returns and the stochastic variance enters similar to a jensen's inequality term

[11] I do not assume Flow to be normally distributed, but require normal distribution of the product of transaction cost with Flow, which is a quadratic term of Flow, as will be shown below.

typically would scale up its portfolio[12]. One can easily calculate the aggregate amount of each asset n that should be bought or sold by funds at time t, were they all to simply expand or reduce their portfolios to match flows while keeping portfolio weights constant. Let $\delta_{i,n,t}$ be the weights of the trading portfolio[13]. The aggregate traded amount of each asset is calculated as:

$$AFlow_{n,t} = \sum_{i=1}^{I} \delta_{i,n,t} Flow_{i,t}$$

where $\sum_{n=1}^{N} \delta_{i,n,t} = 1$ for all funds $i = 1 \dots I$.

When aggregating expected flows it holds that the expectation of the size of the aggregate trade in the next period is zero, so $E^t[AFlow_{n,t+1}] = 0$. Since portfolio weights $\omega_{i,n,t}$ are the optimal weights at time t it follows that $E^t(\delta_{i,n,t+1}) = \omega_{i,n,t}$. When actually trading at t+1, fund managers choose the actual $\delta_{i,n,t+1}$ trading portfolio weights[14].

Next, I model liquidation cost $c(\cdot)$ as a function of the aggregate transaction for each asset at t. For simplicity let us assume it to be a linear function of the form $c(AFlow_{n,t}) = a + b \cdot (\sum_{i=1}^{I} \delta_{i,n,t} Flow_{i,t})$ and set $a = 0$, ignoring fixed trading costs. Hence, all assets can be traded costless in very small

[12]Liquidity considerations aside, the amount of money managed by the fund should not change its portfolio choice. For a discussion see Bhushan (1992). Furthermore, empirical evidence in support of scaling has been presented by Lou (2010).

[13]Defined as: $\delta_{i,n,t} = \omega_{i,n,t} + (\omega_{i,n,t} - \omega_{i,n,t-1}) \frac{W_{i,t-1}}{Flow_{i,t}}$ since it must hold that $\delta_{i,n,t} Flow_{i,t} = \omega_{i,n,t} W_{i,t} - \omega_{i,n,t-1} W_{i,t-1}$. For zero flows the trading portfolio does not exist and trading portfolio weights are undefined.

[14]There are 3 distinct cases: For $\omega_{i,n,t} = \delta_{i,n,t+1}$ the portfolio weight does not change, the fund is simply scaling up/down its previous position. For $\omega_{i,n,t} > \delta_{i,n,t+1}$ the fund trades less of asset n than in the case of scaling. With positive (negative) $Flow_{i,t+1}$ this means that the fund reduces (expands) its relative position in the asset. For $\omega_{i,n,t} < \delta_{i,n,t+1}$ the fund trades more of asset n than in the case of scaling. With positive (negative) $Flow_{i,t+1}$ this means that the fund expands (reduces) its relative position in the asset.

quantities, while only aggregate volume has an effect on the cost of trading. The multiplier b can be understood as indicating the absolute value of liquidity-trading driven return per \$ volume traded, similar to the Amihud-measure of an asset[15]. Depending on the sign of $AFlow_{n,t}$, $c(\cdot)$ can be positive or negative. In this framework a "negative cost" can be understood as an additional return rewarding provision of liquidity.

So, realized returns on asset n consist of 2 components; the return $r_{n,t}$ from the fundamental value of the asset, minus the cost of trading c, both to be realized at the end of each period. If a fund does not trade a particular asset, it realizes only its fundamental return $r_{n,t}$ as it keeps holding the asset in the portfolio and I assume that the asset price returns to its fundamental value after everyone has traded. For each unit of the asset traded the fund realizes $r_{n,t}$- $c(\cdot)$. This incurred trading cost then gets diluted over the entire position, so even fund-investors that have not caused outflows suffer as their share of the fund looses value due to the dilution of cost[16].

I model the portfolio choice as a pure investment problem incorporating the above described transaction cost from stochastic flow induced trading[17]. Each fund i maximizes expected utility of its investors over their future wealth according to the following maximization problem:

$$\max_{\omega_{i,1\ldots N,t}} E_t U \left[W_{i,(t+1)} \right] =$$

[15]To simplify the theoretical setup I assume b to be constant across all assets. A nice extension of this model would be to allow for an endogenous b_n as this way liquidity cost would be determined by portfolio choice and correlation in flows.

[16]This actually might cause a type of "run" on the fund in the spirit of Bernardo and Welch (2004) when fund investors expect a significant mass of others to redeem their share in the fund.

[17]I assume that there are no conflicts of interest between fund-managers and investors in this delegated investment management setup.

$$= \max_{\omega_{i,1\ldots N,t}} E_t U\left[\sum_{n=1}^{N}\left[\omega_{i,n,t}(1+r_n)-\delta_{i,n,(t+1)}Flow_{i,(t+1)}\,c(AFlow_{n,(t+1)})\right]\right] \tag{1.1}$$

$$\text{s.t. } \textstyle\sum_{n=1}^{N}\omega_{i,n,t} = 1, \qquad \omega_{i,n,t} \geq 0, \qquad \forall i,n,t$$

Short selling is restricted and funds have to invest their entire capital into the portfolio. Each fund's initial wealth under management is normalized to 1. Flows have to be seen as fund investors moving money between their cash holdings and their mutual fund portfolios, so they are not added or subtracted from wealth in the maximization problem. There exists a riskfree asset with return r that can be traded costless. The cost component in equation (1.1) is calculated by the cost function $c(\cdot)$ that depends on the aggregate volume of asset n traded by all funds in the market, multiplied by $\delta_{i,n,t+1}Flow_{i,t+1}$, which is the dollar amount of asset n traded by fund i at $t+1$. This equals the total liquidity loss (gain) in dollar terms at time $t+1$, since the loss (gain) from the trade gets diluted over the entire position. This, as wealth is normalized to 1, equals the portfolio weighted return of the position. Using iterated expectations we can replace $\delta_{i,n,t+1}Flow_{i,t+1}$ with $\omega_{i,n,t}Flow_{i,t+1}$.

The N first order conditions of equation (1.1) for each fund i yield:

$$E\Big[U'(W_{i,t+1})[(1+r_n) - Flow_{i,t+1}\,c(AFlow_{n,t+1})]\Big] =$$
$$= E[U'(W_{i,t+1})(1+r)]$$

where r denotes the return on the riskfree asset. Assuming normal distribution of investor wealth, asset returns and transaction cost, the expected realized excess period return $\tilde{\mathrm{R}}$ for fund i over asset n is[18]:

$$\begin{aligned}
& E[\tilde{R}_{i,n}] = \\
= \quad & E[r_n - Flow_{i,(t+1)}\, c_{n,(t+1)}(AFlow_{n,(t+1)}) - r] = && (1.2) \\
= \quad & -\frac{E[U''(W_{i,(t+1)})]}{E[U'(W_{i,(t+1)})]} Cov(W_{i,(t+1)}, r_n) + && (1.3) \\
+ \quad & \frac{E[U''(W_{i,(t+1)})]}{E[U'(W_{i,(t+1)})]} Cov\Big(W_{i,(t+1)}, Flow_{i,(t+1)}\, c(AFlow_{n,(t+1)})\Big)
\end{aligned}$$

Equation (1.2), when using the linearity assumption for the shape of the cost function c, yields:

$$E[\tilde{R}_{i,n}] = E[r_n - r] - bCov(Flow_i, AFlow_n) \tag{1.4}$$

Equations (1.3) and (1.4) show the conditional expectation of fund i for the realized excess return R̃ on asset n. Note that this is not a pricing equation as I have not imposed market clearing so far. It is merely the expected realized return conditional on the contemporaneous trading pattern of fund i. When averaging across assets (1.4) the expected realized excess portfolio return of fund i becomes:

$$E[\tilde{R}_i] = \sum_{n=1}^{N} \omega_{i,n}\big(E[r_n - r]\big) - E\big[bCov(Flow_i, PFlow_i)\big] \tag{1.5}$$

where portfolio level flow for fund i is calculated as:

$$PFlow_i = \sum_{n=1}^{N} \omega_{i,n} AFlow_n$$

Aggregating equation (1.3) across agents and averaging across assets yields the unconditional expectation of the realized excess return on the market portfolio for the average fund.:

$$\begin{aligned}
E[\tilde{R}_m] \quad &= \quad E[r_m - r - b\sigma^2_{MFlow}] = && (1.6) \\
&= \quad -\frac{E^i[U''(W_{m,(t+1)})]}{E^i[U'(W_{m,(t+1)})]}\sigma^2_{r_m} + \\
& \quad\quad +\frac{E^i[U''(W_{m,(t+1)})]}{E^i[U'(W_{m,(t+1)})]} b^2 Var(\sigma^2_{MFlow})
\end{aligned}$$

[18]Using: $E[\tilde{A}\tilde{B}] - E[\tilde{A}]E[\tilde{B}] = Cov(\tilde{A}, \tilde{B})$ and $Cov(f(\tilde{x}), \tilde{y}) = E[f'(\tilde{x})]Cov(\tilde{x}, \tilde{y})$ assuming normally distributed $\tilde{x}$ and $\tilde{y}$.

It can be seen that if there are many funds with i.i.d. flows, the variance of the aggregate flow in the market $MFlow$ will be zero in the limit as liquidity trades of individual funds cancel each other out. Traders on average will realize simply the fundamental market return r_m^*. As soon as trading shows some systematic component across fund flows, the variance term becomes positive and realized returns on trading the market portfolio are reduced, on average, by the variance multiplied with the sensitivity of stock returns to volume. For each stock n the unconditional realized return for the average trader is:

$$
\begin{aligned}
E[\tilde{R}_n] &= E[r_n - r - b\sigma^2_{AFlow_n}] = \qquad (1.7)\\
&= \left(E[r_m - r - b\sigma^2_{MFlow}]\right)\left[\frac{Cov(r_m, r_n)}{\sigma^2_{r_m} - b^2 Var(\sigma^2_{MFlow})} - \right.\\
&\quad \left. - \frac{b^2 Cov(\sigma^2_{AFlow_n}, \sigma^2_{MFlow})}{\sigma^2_{r_m} - b^2 Var(\sigma^2_{MFlow})}\right]
\end{aligned}
$$

When summing across agents I implicitly assume market clearing, so the above becomes a pricing formula determining the fundamental return r_n, which will be different from r_n^* in the case with no aggregate flow variation. The first notable fact is that the market risk premium is smaller than without liquidity trading cost[19]. Next, we see that expected realized returns decrease in commonality of the liquidity risk from $AFlow$ with respect to market liquidity risk $MFlow$. Finally, investors demand a premium of $b\sigma^2_{AFlow_n}$ to be compensated for the expected loss from trading.

Agents with negative flow correlation to the aggregate flow of an asset will realize additional positive returns over the fundamental return. Yet, if these agents are funding constrained they cannot absorb all the liquidity risk, otherwise they would smooth out aggregate flows until the variance of $AFlow_n$ becomes zero and expected returns equal expected no-flow fundamental returns r_n^*. In equilibrium, the price of asset n has to decrease, so

[19]This result is in line with Jacoby, Fowler and Gottesman (2000), who derive a CAPM for expected realized returns with stochastic bid-ask spreads.

$E[r_n - r] > E[r_n^* - r]$. The expected realized excess return for the average agent with i.i.d. trading pattern is greater or equal to the return in the equilibrium without losses from systematic liquidity trading, so the expected fundamental return of the asset has increased. The important result obtained here is that asset prices are related to the systematic component of trading needs of the current holders of the asset.

This result is fundamentally different from liquidity capital asset pricing models (LCAPM) such as the pricing model introduced by Pastor and Stambaugh (2003). In the LCAPM approach the level of market liquidity is considered a priced risk factor and investors are rewarded for different types of correlation between the (fundamental) return of an asset and the respective liquidity factor. So, for example, an asset which yields high returns in a low-liquidity state of nature will be priced at a premium in the LCAPM. In contrast in the model described here, no priced liquidity market factor exists. Agents demand a premium to hold assets, which are currently held by an investor group whose aggregate flow has an expected non-zero variance. Nevertheless, agents are only able to demand such premium if the variance in the aggregate flow is specific to the asset. The second covariance term on the right hand side of Equation 1.7 reduces the premium that can be demanded for aggregate flow variance risk if such risk is correlated to market-level variance in flows. This means basically that an investor is not compensated for aggregate liquidity risk in the market. Meanwhile, the investor can demand a premium for holding an asset whose aggregate investor flow risk exceeds the risk of flow variation in the market.

Assuming market clearing and equilibrium pricing as outlined above, let us look again at Equations 1.4 and the left hand side of 1.7 and discuss them in the context of the equilibrium price. For example, fund i holding asset n if $Cov(Flow_i, AFlow_n) > \sigma^2_{AFlow_n}$ means that fund i has to pay for having excess correlation between its flows and the aggregate portfolio weighted flows of asset n. On the other hand, assets where $Cov(Flow_i, AFlow_n) < \sigma^2_{AFlow_n}$ will yield additional excess returns to the respective fund, since it becomes a relative liquidity provider. A fund should therefore increase its portfolio weights in such assets. From this I infer $Cov(Flow_i, PFlow_i) \leq \sigma^2_{PFlow_i}$ to be the upper bound of optimal flow correlation at the portfolio level. Each fund should be able to find a portfolio where the covariance between its flow and the portfolio weighted average flow is at least equal but not greater than the variance of the portfolio flow itself. Nevertheless, as I do not impose a particular underlying flow structure it is not possible to calculate the lower bound, which should be the portfolio that yields the highest excess return due to liquidity provision by the fund and should therefore automatically be the optimal portfolio. Normalizing the upper bound covariance, the respective upper bound correlation coefficient is:

$$\rho_{Flow_i, PFlow_i} \leq \frac{\sigma_{PFlow_i}}{\sigma_{Flow_i}} \tag{1.8}$$

A couple of properties should be discussed. First, the lowest possible upper bound is zero, which is the case where individual flows cancel out the aggregate flow and its standard deviation becomes zero. In this case the correlation coefficient also goes to zero. For funds with very small flows the upper bound becomes very large. In this case the fund will not incur much liquidity related losses due to the small size of its liquidity trading even though flow dynamics can be quite highly correlated with aggregate flows. A similar upper bound can be derived for each asset/fund combination. It can be expected that a fund will only buy a particular asset for which its correlation exceeds the upper bound if the fund manager believes that the asset is mispriced and will at least yield an additional expected return of $b(Cov(Flow_i, AFlow_n) - \sigma^2_{AFlow_n})$ due to the mispricing. So, in case assets are commonly believed to be undervalued, an increase in flow correlation should be observable.

Equilibrium

From the above reasoning for the existence of an optimal upper bound one can conject that for each possible variance-covariance matrix of flows there exists at least one corresponding pareto-optimal equilibrium allocation with regard to losses from parallel trading. This equilibrium is achieved once all agents adjust their portfolios to remain below the optimal upper bound. The upper bound of one agent is affected by the portfolio choice of the other agents with whom he has non-zero funding flow correlation. In the case where all agents hold portfolios with $\rho_{Flow_i,PFlow_i} \leq \frac{\sigma_{PFlow_i}}{\sigma_{Flow_i}}$ the upper and lower bounds converge and become equal to the agents' portfolio-adjusted flow correlation coefficient $\rho_{Flow_i,PFlow_i}$. This is due to the fact that if all agents hold portfolios where they do not make losses from to simultaneous trading beyond the level that is priced in the market other agents can not achieve additional gains from contemporaneously providing liquidity to their peers. Hence, the upper and lower bounds converge, a pareto improvement becomes impossible and a pareto optimal equilibrium is achieved. Once all agents hold such portfolios, for any additional agent entering this economy a portfolio-indifference result holds, similar to the equilibrium result outlined in Wagner (2008). Each portfolio gives the same expected return after cost from simultaneous trading is taken into account. In the equilibrium described above, all portfolios must give the same level of expected utility, since otherwise investors holding portfolios with lower utility would switch. Therefore, in such an equilibrium, a new - price-taking - investor is indifferent between portfolios, regardless of his or her fund flow correlation with others[20].

[20]This argument purely concerns portfolio returns regarding losses from liquidity induced trading, other classic portfolio diversification preferences obviously still apply

Empirical Tests

In this paper I do not test the asset pricing implications of the model described above, but am rather interested in the impact of flow correlation on mutual fund performance as described in Equation 1.4. I introduce a measure of portfolio-adjusted flow correlation (PFC), representing the covariance term of Equation 1.4 and test if there is a negative relationship between expected risk-adjusted returns of a fund and its level of PFC. Furthermore, I test if fund managers hold non-optimal portfolios with respect to the theoretical optimal upper bound of flow correlation derived above. For future work it would be interesting to directly test the asset pricing and equilibrium implications of the model with respect to correlation in trading needs.

1.4 Data and Sample Selection

In this study I use 3 distinct databases, namely the CRSP Survivorship Bias Free Mutual Fund database, the CDA/Spectrum Mutual Fund and Investment Company Common Stock Holdings Database provided by Thompson Reuters, and the CRSP database on common US stocks. The sample being used spans the period January 1990 to December 2008[21].

The CRSP Mutual Fund database contains monthly information about funds' total net assets under management (TNA), fund returns, equity ratios and cash holdings for each share-class of the fund. Monthly fund-returns reported in CRSP are net returns, after fees etc., but before any front-end or back-end loads. Following standard literature, I assume implicitly that funds' flows occur at the end of each month, so I calculate monthly flows in and out of funds aggregated to fund level as:

$$FLOW_{i,t} = TNA_{i,t} - TNA_{i,t-1} * (1 + r_{i,t})$$

[21]For the period 1980-1989 quarterly data of flows is available, but I do not to use it due to the lower quarterly frequency.

where $TNA_{i,t}$ are total net assets held by fund i at time t and fund $i's$ returns $r_{i,t}$ are returns realized in period $[t-1, t]$. I correct for mergers, subtracting the final TNA of the dying fund from the $FLOW$ of the surviving fund during the month of the merger. Since information about merger dates in CRSP is not very precise I use a matching procedure to select the month with the highest flow at the acquiring fund as the true month of the merger within a 6-month window $[t-1, t+5]$ around the reported merger date. Subsequently, as I am interested in the analysis of correlation of flows, I delete the first and last flow observation for each fund. These flows are equal to the initial and final TNA of a fund, and since funds initiate and terminate at random times their initial and final flows are not correlated with flows of their peer funds. Additionally, I correct the database for obvious digit entry errors of total net assets by using a procedure to identify subsequent inflows and outflows of the same order but reversed sign due to an outlier in TNA of an order of magnitude of 10 (or 0.1) compared with previous and subsequent TNA values. To avoid removal of correct entries by this procedure I check if the absolute value of the calculated flow created by the erroneous TNA observation is at least 3 standard deviations away from the funds' flow average in order for the erroneous TNA to be removed. The above described procedure and merger correction appear to eliminate almost all of the extreme outliers in the flow distribution. In order to address issues regarding fund incubation bias, I exclude the first 12-month fund returns[22], which also addresses any concerns that new funds might be cross-subsidized by their respective fund families[23]. I further winsorize the dataset by deleting merely the 0.1% and 99.9% extreme tails. Finally, I only include funds with minimum TNA of 1M$ in the sample.

Thompson Reuters' CDA/Spectrum Mutual Fund database contains data on mutual fund portfolio holdings. The reporting

[22] See: Elton, Gruber and Blake (2001) and Evans (2004)

[23] Gaspar, Massa and Matos (2006)

frequency is quarterly for most funds in the sample. Since CDA bases its information on the holdings file date, and not the actual reporting date, for which the holdings are valid, I correct stock prices and adjust for eventual stock-splits between reporting and file date. Finally, I merge CRSP and CDA using the MFLINKS tables provided by Wharton Research Data Services (WRDS). As the CDA database reports holdings on fund level, not by fund share class, I consolidate CRSP share classes to fund level using the MFLINKS merging table. Fund level returns are calculated as share-class returns value weighted by the TNA of each class, fund level total net assets are the sum of assets of each underlying share-class. To ensure correct mapping I require that the TNA's reported by CRSP and Thompson for each fund do not differ by more that a factor 2 (0.5). Following Lou (2010) I only include US domestic equity mutual funds in the sample, in order to obtain comparable results. I therefore include funds with CDA/Spectrum investment objective code specified as aggressive growth, growth, growth and income, balanced, unclassified or missing. Furthermore, I restrict the sample to funds with an equity ratio between 0.75 and 1.2 [24]. Table A.2 in the Appendix provides the summary statistics of the merged sample.

Data on monthly share prices and returns, bid-ask spreads, volume and shares outstanding is obtained from the CRSP Common Stock Holdings database. I exclude stocks priced below $5, as is common practice in order to avoid microstructure noise. Furthermore, I employ the three Fama-French risk factors and the momentum factor, all provided by Prof. Kenneth French, to calculate fund- and portfolio alphas using 48-month rolling windows. Additionally, I calculate the monthly Amihud liquidity measure[25] for each stock using a 48-month rolling window. The relative Bid-Ask spread is computed as bid-price minus ask-price divided by the mid-price. Finally, I calculate the normalized

[24] See discussion Cremers and Petajisto (2009).

[25] See Amihud (2002).

monthly Herfindahl Index of portfolio concentration for each fund as:

$$H_{i,t} = \sum_{n=1}^{N_i} \omega_{i,n}^2$$

$$H_{i,t}^* = \frac{H - 1/N_i}{1 - 1/N_i}$$

1.5 Portfolio-Adjusted Flow Correlation Measure (PFC)

It has been shown that flow induced trading by mutual funds creates price pressure on individual stocks. Coval and Stafford (2007) show that extreme fund flows lead to significant drops in share prices, while Lou (2010) shows that price pressure from flow induced trading is predictable on a stock level. Here I create a correlation measure that allows a fund to know its exposure to simultaneous flow induced trading by peer funds. In particular, I construct a measure of correlation between the flows of an individual base fund and the portfolio weighted sum of flows of its peer funds holding overlapping positions. Basically, a fund manager that does not buy or sell assets should not be concerned about price variation in her portfolio due to other funds' flow induced trading. Price drops due to peer funds' liquidity trading today mean higher returns tomorrow, as there is no change to assets' fundamentals. A problem arises if said fund manager is forced to sell assets due to withdrawals from her fund while the asset price is depressed. Equally, a fund benefits greatly from inflows if it is able to buy assets cheap, while other funds are forced to sell them.

What does this mean for a fund manager's portfolio choice? Holding assets that are subject to flow induced price drops will be costly for a fund if these drops are contemporaneously correlated with the fund's own outflows. As is shown in Equation 1.8, there exists an upper bound of portfolio adjusted flow correlation that should not be exceeded in order to avoid costs from simultaneous liquidation. A fund manager should therefore rebalance her portfolio by decreasing holdings of assets which lead to exceedance of this bound. The PFC measure is the portfolio-adjusted flow correlation that can be compared against the upper bound at the fund portfolio level.

The idea behind the PFC measure constructed here is to have an indicator for the level of flow induced unidirectional contemporaneous trading by peer funds inherent in fund portfolios. In a way, choosing a portfolio with a certain flow correlation means choosing a level of liquidity timing. A manager holding a high PFC portfolio exhibits negative timing, so she would systematically sell cheap and buy expensive. A zero PFC portfolio would mean no liquidity timing, in this case assets are bought and sold - on average - at their fair value, as far as mis-pricing due to flow induced trading is concerned. Negative PFC is equivalent to a manager who possesses positive liquidity timing ability, where assets are being bought cheap and sold expensive as the fund provides liquidity to its peers.

To construct the PFC, I first calculate the aggregate amount of each asset n that should be bought or sold by funds at time t, were all funds to simply expand or reduce their portfolios to match flows while keeping portfolio weights constant. Mutual funds typically scale their portfolios up and down with inflows and redemptions (see e.g. Bhushan (1992)). Lou (2010) estimates a partial scaling factor to be 0.97 for outflows and 0.62 for inflows. This means that funds facing redemptions almost perfectly scale down their portfolios, while with inflows on average 62 cents per Dollar gets invested into the existing portfolio. In a first stage, assuming near-perfect scaling, I construct backward looking 48-month rolling windows for each asset, summing the flows of all fund's currently holding the asset[26] multiplied with the current

[26]These flows do not represent the actual past trading of the asset, they

portfolio weights in each fund's portfolio.

$$AFLOW_{n,t,[t..t-47]} = \sum_{i=1}^{I} \omega_{i,n,t} * FLOW_{i,[t..t-47]}$$

This leads to 1.331.781 distinct 48-month asset-level flow windows. As a second step, I aggregate the asset flow windows into portfolio flow windows for each fund-month observation, weighing the asset flows with the current portfolio weights of each base fund.

$$PFLOW_{i,t,[t..t-47]} = \sum_{n=1}^{N} \omega_{i,n,t} * AFLOW_{n,t,[t..t-47]}$$

Finally, I calculate the correlation coefficient between the aggregate portfolio flow window and the corresponding 48-month fund flow window for each fund/month observation, given an existing 48 month flow history for the base fund.

$$\rho_{i,t} = \frac{Cov(PFLOW_{i,t,[t..t-47]}, FLOW_{i,[t..t-47]})}{\sigma_{PFLOW_{i,t,[t..t-47]}} \sigma_{FLOW_{i,[t..t-47]}}}$$

From the before mentioned sample I end up with 163,642 fund-month estimates of the PFC.

By way of construction, I expect the PFC to systematically underestimate the real absolute value of correlation. This is due to the fact that not all funds currently holding an asset have a flow history of up to 48 months. So, when adding up flows with current portfolio weights, peer funds with a flow history shorter that 48 months are underweighted in the correlation measure. Nevertheless, excluding funds with shorter flow history might distort the measure even more, since more recent flows are more indicative. Reducing the length of the estimation window mitigates this problem, while at the same time adding to the estimation error in the correlation measure. As a robustness check I have run

are value weighted past flows $[t..t-47]$ of the funds holding the asset at time t

the analysis using shorter 24 and 12 month estimation windows, obtaining largely consistent results. As this problem supposedly can only, if anything, weaken my results, I prefer the measure with smaller estimation errors and longer window size and report everything based on 48-month windows, keeping the downward bias in mind when analyzing my results.

The portfolio flows contain the 48-month flow of the base fund itself, which increases the PFC significantly when assets are mostly held by just the one fund. One could, of course, first subtract the base fund flow from the portfolio flow, creating portfolio flow windows that only contain weighted peer fund flows, before calculating covariance matrix. Nevertheless, since I am interested in the liquidity management of fund managers, keeping the base fund's own flow in the portfolio flow gives a clearer picture. If a fund holds a non-overlapping portfolio of - probably small-cap - stocks, then its correlation measure would be positive and close to 1. As there are no other funds trading in these particular stocks, the fund will face a significant price discount when trying to wind down its position. Hence, it is subject to its own flows inducing price pressure.

Table A.1 reports mean, median, skewness and extreme values of the PFC measure. It is remarkable that during the early 90s there was a slightly higher level of portfolio flow correlation than in the second half of the sample. Skewness is positive for most years. Figures 1a and 1b show the distribution during the 90's and 00's. The mass of correlation lies around 0.15-0.25 with some funds also having negative PFC. It is interesting to see that the skewness of the PFC measure appears to be dramatically lower during crisis times than during non-crisis periods. In 1997-1998 during the Asian/Russian crisis and LTCM as well as in 2002-2003 after the burst of the internet bubble the distribution of the correlation measure has less positive skewness, so fewer funds appear to hold high-correlation portfolios.

1.6 Empirical Results

Determinants of the PFC Measure

Mutual Funds have to be seen as investment conduits. Individual investors put their moneys into funds while seeking a particular investment style or sector or chasing past fund performance, or manager skill (see Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998)). This of course means that similar funds making similar investments will have similar flows and hence high funding flow correlation. There exists therefore some endogeneity of the level of flow correlation from the portfolio choice. Edelen (1999) finds that there is substantial positive cross-correlation in fund flows indicating common factors affecting flow. But how similar do fund portfolios have to be in order to attract simultaneous flows? And how much freedom does a fund manager have in managing dynamic liquidity? In this section I examine to which extent portfolio and fund characteristics are determinants of portfolio-adjusted funding flow correlation. Table A.3 reports the characteristics of portfolios held by mutual funds in the sample period January 1994 to December 2008, as well as separated by decade. It can be seen that average portfolio weighted fund flow correlation in the 1990's was slightly higher than in the 2000's. Funds' excess returns, while being higher in the later decade, are slightly negative at around -10 to -18 basis points monthly, calculated as 3- and 4- factor alphas after fees, but before front- or back-end loads. Considering that these are well-diversified portfolios, holding around 100+ different stocks on average, a market beta of close to 1.0 is to be expected. Furthermore, it can be observed that funds on average have some positive load on the size factor, but typically do not have a load on neither momentum nor the value factor. Figures 2 - 4 show the distribution of factor loadings at the portfolio level. The size factor seems to have a wider, flatter distribution between 0.0 and 1.0, yet with a concentration of mass around -0.1, which indicates that a significant group of funds does not follow a size-factor strategy and does not invest into very small stocks. The load on the value-HML factor is centered around 0.0 but with a relatively large standard deviation. On the other hand, momentum appears much more narrowly centered around 0.0, so not many funds actually appear to be actively trading pure momentum or contrarian strategies.

Next, I analyze the determinants of PFC ($\rho_{i,t}$) at the portfolio level. Portfolio and fund characteristics are expected to influence the level of flow correlation, yet if there is large unexplained variability, this would mean that the fund manager has certain freedom to manage the level of flow correlation. I run the following regression to determine which factors influence flow correlation:

$$\begin{aligned}\rho_{i,t} &= \alpha + \beta_1 B_{MKT,i,t} + \beta_2 B_{SMB,i,t} + \beta_3 B_{HML,i,t} + \beta_4 B_{MOM,i,t} \\ &\quad + \beta_5 Log(Ami_{i,t}) + \beta_6 Log(Herf_{i,t}) + \beta_7 Age_{i,t} \\ &\quad + \beta_8 SampleMonth_t + \beta_9 Lag(ExRet)_{i,(t-1)} + \epsilon_{i,t}\end{aligned}$$

Table A.4 reports the determinants of the PFC measure as results of pooled-OLS[27] regressions using the 3 Fama-French and the momentum factor loads as well as the Amihud measure of portfolio liquidity, the Herfindahl index of portfolio concentration, the fund's age is included to account for fund growth effects such as fund's size[28], reputation, imitation by peer funds, etc., a month-index of the sample period to capture fixed time effects and the 1-month lag of the excess return as the fund alpha of a 4-factor Carhart model. The intercept shows the average flow correlation at around 0.28, with a declining time trend, reported by the negative coefficient for the sample month index.

[27]Results are robust to using a Fama-MacBeth approach instead of pooled-OLS

[28]It might be prudent to include size as a regressor, which should be rectified in future versions of this paper. Nevertheless, as fund age and size are highly correlated, results are not likely to change much with regard to the total explanatory power of the regression model.

Load on the SMB factor is positive and significant, with a coefficient of around 0.15. The higher the load on the factor, the higher is flow correlation. This confirms expectations, as funds following the same investment strategy are bound to hold overlapping portfolios while having high correlation in their flows, such as is the case with the size factor coefficient. Nevertheless, the Book to Market Value HML factor and the Momentum factor do not appear to be significantly correlated with the PFC measure. After examining the reason for the weak relationship between flow correlation and these risk and momentum factors, I find that for funds with high factor loads (factor tracking funds), the respective factor load becomes highly significant as a determinant of flow correlation. The last column of Table A.4 reports regression results for funds with dummy variables for high risk factor loads, one standard deviation or more above the average. When conditioning on extreme loads for the size factor nothing changes in relation to the unconditional regression specification. But, both the HML-value and momentum factor loads significantly affect flow correlation for funds whose returns are strongly determined by the respective factor. Adjusted R^2 increases to up to 9.4%. In the related study of Frazzini and Lamont (2008) they show that their flow based measure of investor sentiment is highly correlated to the value factor, reporting positive flows into mutual funds that own growth stocks and out of funds that own value stocks. They argue that this investment pattern is not only nonrational but also destroys wealth of mutual fund investors. It is reasonable to assume that investor sentiment causes the higher flow correlation observed for funds with high factor load. Finally, the coefficient for the market risk factor is positive and significant but very close to zero in the regression model without high-factor load dummies. When including the dummies the market risk factor coefficient becomes negative and significant, but remains close to zero.

Portfolio illiquidity co-moves with flow correlation, as the coefficient for the Amihud-measure is positive and significant. A high Amihud-measure means larger price movement per dollar traded. This is bad news for investors as it exacerbates losses from simultaneous trading. The coefficient for portfolio concentration using the logarithm of the adjusted Herfindahl index is also significant. This means, the more concentrated the portfolio is, the higher is the flow correlation exposure to the fund. This has been expected, since a less diversified fund is bound to have higher correlation. Flow correlation increases by 0.06 for each increase by one-standard deviation in log(Herfindahl). The Herfindahl index appears to have the highest explanatory power in this regression model. Furthermore, correlation very slightly increases with the age of the fund.

Finally, I find a significant relationship between the cumulative past 12-month fund alpha and flow correlation. A positive alpha is a strong signal which attracts investment inflows, additionally funds holding such "winning" portfolios are unlikely to rebalance their holdings. Peer-funds with available funds/inflows are likely to imitate and to tilt their portfolios towards the "winning" portfolio. Both leads to an increase in PFC. Equally, fund holding a "loosing" portfolio with strongly negative past alpha are likely to have simultaneous outflows, yet, they will rebalance their portfolios away from the "loosing" portfolio, so their PFC level will drop. So, to summarize, investors chasing past returns, creates flow correlation.

In summary, adjusted R^2 reaches 8.9% when including all independent variables, and 9.4% when also including dummies for high factor loads. This means that, while portfolio and fund characteristics influence the level of flow correlation, there is a large unexplained variability, which means that the fund manager has some freedom to manage the flow correlation of the investment portfolio. I find evidence that fund investors chase high alpha and factor style funds, creating flow correlation. So, funds who choose to invest into a particular factor will have less freedom in choosing their portfolio with respect to adjusting for high flow correlation. Moreover, less liquid, more concentrated portfolios seem to be held with higher flow correlation. While in future versions of this work the regression model should include additional measures such as turnover ratio, expense ratio, idiosyncratic risk and size for completeness, the main result here is to show that the explanatory power of a model using a fund's portfolio characteristics with respect to flow correlation is low, which means that a fund manager is able to independently control the level flow correlation in his portfolio.

PFC and Investor Return

In this section I analyze the relation between portfolio-adjusted flow correlation and future fund risk-adjusted excess returns. Returns are cumulative and are defined as the return in excess of the risk free rate, as well as alpha from 3-factor Fama-French and 4-factor models including momentum. Table A.5 shows the results forming fund decile portfolios sorted by flow correlation. D1 is the portfolio of funds with the lowest, in this case negative, flow correlation coefficient, D5 and D6 are the median portfolios[29] and D10 is the portfolio of funds with the highest level of flow correlation. The left panel shows the results when re-sorting the cross-section of funds into deciles each month, while in the right panel all fund-month observations have been pooled before constructing decile portfolios. It can be observed that there is no significant unconditional difference between high and low correlation portfolios. Nevertheless, the D5 portfolio, which contains funds for which flow correlation with their peers is very close to zero, outperforms both positively and negatively correlated funds. A t-test for difference in means is significant at a 5% level for the 12-month horizon. Theoretically, one could have expected to see a significant difference in returns also between D1

[29]For simplicity, I subsequently report results for D5.

and D10, but this sorting does not take any additional portfolio characteristics into account. In order to better understand the impact of flow correlation on performance, funds must be compared within peer groups with similar investment styles. I use an approach similar to Daniel, Grinblatt, Titman and Wermers (1997), sorting funds into 125 groups by matching them across 3-style quintiles. I define the quintiles by the factor loads on size, value and momentum of fund returns. Then, within each style group, funds are aggregated into decile portfolios according to their level of fundflow-correlation. Table A.6 reports the results for 1, 3, 6 and 12-month out-of-sample cumulative 4-factor excess returns. It can be seen that the average difference in returns between the top and bottom deciles of flow correlation within each style are not significantly different from zero when averaging over the all style groups.

As this result is not in line with the theoretical expectation of monotonically decreasing risk adjusted excess returns with respect to flow correlation, I analyzed results on a style-group-level. 71 of the 125 style groups in the sample show a significantly positive difference in cumulative excess return for a 12-month horizon at a 5% confidence level, some groups showing annual differences of up to 12.4%. The 19 of the 25 style groups associated with the highest value factor loads show strong, significantly negative differences in returns between deciles for all horizons. Only 8 style groups not associated with high value factor load show a significantly negative difference in returns, while results are not significantly different from zero for the remaining 21 style groups.

So, by splitting the sample, theoretical expectations are confirmed by the sub-sample of 100 style groups, yet the opposite result holds for the set of style groups with the highest value factor loads. The negative difference in returns for the high value factor groups are driven by the post-2002 bubble period from May 2003-December 2004. At that time a large number of funds appears to trade heavily on the value factor while the market recovers. As (internet-)stocks were undervalued after the burst of the bubble, any liquidity related losses from simultaneous trading were compensated by large excess returns driven by fundamentals. This means that funds with inflows were able to buy undervalued shares, while funds without inflows (and hence with low flow correlation) were loosing out. This period could be a manifestation of a strong "smart money effect" as described by Gruber (1996) and Zheng (1999). When removing this particular interval from the sample, the observed effect disappears. Nevertheless, rather than removing the sample period, I remove the 25 style groups with extremely high loads on the value factor[30].

When averaging over the subsample of 100 styles, it can be seen that funds with lower flow correlation significantly outperform their high-correlation peers for holding periods of 3-months or longer.The average annual difference in 4-factor excess returns between funds with high and low flow correlation is 1.43% after fees and expenses but before loads. Moreover, the results in Table A.6 are robust to splitting the sample into sub-periods.

Additionally, I control for the level of liquidity and portfolio concentration, lagged excess returns as well as fund age and fixed time effects. Table A.7 shows the results of the following regression:

$$\begin{aligned} cumExRet_{i,(t+12)} &= \alpha + \beta_1 \rho_{i,t} + \beta_2 Lag(ExRet)_{i,(t-1)} \\ &\quad + \beta_3 Log(Ami_{i,t}) + \beta_4 Log(Herf_{i,t}) \\ &\quad + \beta_5 Age_{i,t} + \beta_6 Log(FundSize)_{i,t}) \\ &\quad + \beta_7 SampleMonth_t + \epsilon_{i,t} \end{aligned}$$

It can be seen that previous results hold, with a negative and significant regression coefficient of -1.44% for flow correlation, con-

[30]Excluding these high-factor-load funds seems prudent since in the previous section it has been shown that once factor loads are very high, a fund-manager has much less flexibility in managing dynamic liquidity but has to follow the herd instead.

firming its predictive power for out of sample long horizon excess returns. Portfolio concentration is positive and significant, so less diversified managers appear to achieve higher returns compared to their more diversified same-style peers. Fund size is not a significant predictor of fund returns once PFC is introduced. Chen, Hong, Huang and Kubik (2002) find that size is a significant inverse predictor of mutual fund returns and offer two explanations that would lead to an erosion of performance with fund size, namely liquidity and organizational diseconomies. The finding that size is not a significant performance predictor once introducing the PFC measure can be seen as additional evidence supporting their liquidity argument. Adjusted R-square is 7.53%. Results are robust when splitting the sample into 2 sub-periods.

PFC and Portfolio Choice

In this section I examine if funds select their portfolios optimally to stay below the upper bound of portfolio correlation shown in Equation 1.8. The aim is to examine if there is a difference between funds regarding their portfolio choice with respect to the bound and to estimate the proportion of "skilled" funds. Table A.8 shows the median upper bound in the sample, the median value by which funds exceed their respective upper bound and the proportion of funds that hold portfolios where the portfolio flow correlation exceeds the theoretical upper bound of optimal portfolio choice. It can be seen that the average proportion of funds exceeding the bound is 31.4%. I estimate exceedance to be significantly higher in the first half of the sample than in the second half. Moreover, the median distance between the bound and flow correlation has decreased from its highest value of +0.12 in 1994 to -1.36 in 2004. So it appears that funds in the second half of the sample seem to be better at finding portfolios where they also provide liquidity to each other instead of herding towards a single strategy.

Still, over 30% of mutual funds hold inefficient portfolios, as far as dynamic liquidity hedging is concerned. Two possible reasons can explain this result. First, these funds ignore flow correlation and systematically destroy investor wealth due flow-induced trading. Second, fund-managers believe in their ability to identify mis-priced stocks whose the additional returns due to mispricing outweighs losses from flow-induced trading in which case managers would rightly ignore excess levels of PFC.

Extensions

In this study I calculate the correlation between the aggregated portfolio flow and fund flows. It would be an interesting extension of this work to break results down one level and calculate the correlation between individual asset flows and the flows of each of the funds holding a particular asset. It would be interesting to see if fund managers of funds with higher alpha actively manage flow correlation in their portfolios. Asset level flow correlation can give insight if managers follow an active or passive flow correlation strategy. One possible approach would be to calculate upper-bound exceedance on fund/asset level and then compare returns between a portfolio of assets where a fund exceeds the asset-level upper-bound with returns from assets held by the same fund without exceeding the respective bound. If there is no significant difference between the two portfolios this can be interpreted as skill with respect to liquidity management, where the manager holds assets with high flow correlation only if such are sufficiently undervalued to make up for liquidity trading losses. To calculate asset-level bounds might also prove a useful practical tool for fund managers to determine whether or not to add a certain asset into their portfolios. A possible test to distinguish between an active versus passive flow correlation strategy would be to split the sample between high and low liquidity periods and test for differences in PFC levels between the two. An active strategy would result in lower levels of PFC in the low liquidity regime (or in anticipation of such).

An additional extension to this chapter could be a breakdown of results for concentrated versus diversified funds as well as liquid versus illiquid portfolios, since it has been shown that both of these parameters highly influence the portfolio flow correlation statistic.

Also, two alternative specifications of the PFC as performance predictor should be investigated and benchmarked against the PFC presented in this work. First, the difference between the actual level of PFC and the upper-bound should be a better performance indicator than the absolute level of the PFC. The further the level of PFC is below the bound, the more a fund should gain from liquidity provision, while a fund exceeding the bound means that the fund pays its peers a premium for liquidity. Since the upper-bound depends on the fund portfolio, an certain absolute level of PFC might mean bound exceedance for one fund, while another fund with the same level of PFC may be far below its respective bound. In the work presented here I am controlling for such a problem using a style-matching procedure, but I think that a difference measure between the bound and PFC would give a more immediate result. A second alternative specification could be using the residuals from the regression of Table A.4 instead of the PFC measure. The regression model estimates the level of inherent flow correlation due to portfolio and fund characteristics, so the residuals from the regression are a measure of "voluntary" flow correlation taken by the fund. Since these residuals are orthogonal to portfolio and fund characteristics, it is not necessary to style match funds when using the residuals as performance predictors.

Additional Robustness

A possible source of concern regarding the construction of the PFC measure is the use of current portfolio weights when multiplying historic flows. Therefore, as a robustness check, I estimated PFC using historical weights instead of current weights and found that the correlation coefficient between the 2 different estimators is extremely high, at 0.93. Considering such a high level of correlation between the two estimators, and the fact that the use of current weights is required by the theoretical motivation for the PFC measure, I believe using current weights to be prudent, and all results quoted in this study are based on current portfolio weighting. The main reason for choosing current weights is that only these can give an accurate picture of the correlation of overlapping flows between the current holders of assets in a portfolio. Correlation calculated with historical portfolio weights may not necessarily result in a measure with predictive power when it comes to losses due to simultaneous liquidation, since not historical, but only current asset holders can liquidate at the same time. I therefore do not consider the weight selection criteria to be an issue and have decided to use current portfolio weights as a base for calculation. To use a GARCH approach instead to estimate the PFC measure is not possible, as the PFC does not follow any particular time-series process, but rather exhibits a series of discrete jumps every time portfolios are rebalanced.

The distribution of estimates of funds' PFC correlation measures appears to be relatively stable across sub-periods. Figures 1a and 1b show the distribution of PFC for 2 sub-sample periods, while Table A.1 shows the main distribution statistics of the measure for each year in the sample.

Using the PFC correlation coefficient directly as dependent variable in the regression reported in Table A.4 may be problematic, since by definition, correlation can only take values between -1 and 1. To check for robustness I repeated the regression using a Fisher A-Z transformation to construct a new dependent variable, $PFC_{A-Z} = ln(1+PFC) - ln(1-PFC)$. I find statistical significance for exactly the same variables as in the original regression using PFC. For ease of interpretation, I report the original PFC regression with standard errors corrected for heteroscedasticity. For the other results presented in this study this is not an issue as the PFC coefficient is mainly used as an ordinal ranking indicator to sort mutual fund portfolios and the above mentioned Fisher transformation would not change an ordinal ranking.

1.7 Conclusion

In this paper I investigate the impact of correlated trading patterns of mutual funds on fund performance. In particular I address four research questions. Why and how should flow correlation be a determinant in the portfolio choice problem of a fund? Can fund-managers actively influence flow correlation when choosing their portfolios or are they constrained by the actions of fund-investors? What is the impact on mutual fund performance and is it economically significant? Is there a difference in skill between funds regarding the choice of flow correlation, can it be measured, and what proportion of funds select their portfolios optimally with regard to flow correlation?

Addressing the first question, I develop a theoretical model showing that systematically correlated trading patterns between holders of an asset decreases the price of the asset. With regard to optimal portfolio choice I am able to derive an upper bound for flow correlation in portfolios. The equilibrium outcome of the model leads to funds taking diversified and heterogeneous portfolio positions to minimize costs from simultaneous liquidation with peers. In such an equilibrium there are no gains from liquidity provision between funds and losses are uniform and defined by market wide liquidity shocks. Clustered liquidity co-movements lead to a price discount for the assets held by the cluster. These are important results as they show that current asset prices can be influenced by the expected future liquidity needs of the holders of an asset and that correlation with systematic trading patterns should be taken into account in the portfolio choice problem of an agent. In the model I examine the choice problem faced by mutual funds, yet I expect the results to apply equally in a more general setting.

When determining if fund-managers can influence flow correlation when choosing their portfolios I find empirically that portfolio-adjusted flow correlation is determined to some extent by mutual fund investors chasing investment styles and lagged excess returns. I also find that correlation is partially driven by portfolio characteristics such as concentration and liquidity[31]. Yet, with an R^2 of 9.4%, the majority of variation in flow correlation remains unexplained and is orthogonal to style or portfolio characteristics and can therefore be seen as "voluntary" flow correlation.

Addressing the third question, I find significant evidence that flow correlation decreases fund excess returns in the long run, when controlling for fund style. I find that low-correlation funds outperform their high-correlation peers by an annual 4-factor excess return of 1.4% on average.

Finally, I argue that there is a difference in skill between funds regarding their portfolio choice as far as dynamic liquidity is concerned. Using the optimal upper bound of flow correlation to measure portfolio selection skill, I find that on average one third of US-mutual funds hold non-optimal portfolios with excess portfolio-adjusted flow correlation.

[31] When discussing causality in this case, it must be argued that the portfolio held by a fund and the fund's characteristics attract a certain type of investor profile and therefore lead to a certain type of flow, which in turn determines the level of flow correlation. On the other hand, a change in flow correlation is unlikely to lead to a change in fund characteristics. It can therefore be argued that a certain level of flow correlation is caused by fund and portfolio characteristics, while the unexplained portion of flow correlation can be seen as "voluntary".

2 Betas and Liquidity: Differences in systematic price risk due to asymmetric asset liquidity and correlated funding shocks

2.1 Introduction

Financial markets contain assets with different liquidity characteristics, where some assets can be traded more conveniently and at lower cost than others. While standard theory typically assumes costless and frictionless trading, a large body of complementary models has emerged explaining and documenting the effects of illiquidity. This chapter adds to existing research by illustrating a possible link between assets' liquidity and their market risk (Beta) coefficients.

Asset liquidity can be understood as the ease, or cost, of trading a particular asset, while agent- or funding liquidity refers to the cash needs or wealth shocks of an agent or investor. Agents hold and trade assets with different levels of liquidity for different reasons. An investor expecting the need for a large amount of funding liquidity, i.e. a negative wealth shock, will generally hold a portfolio with higher asset liquidity, while another agent might prefer to hold less liquid assets, expecting a longer trading horizon over which trading costs can be spread. So, to an extent liquid assets are traded to absorb funding shocks, while illiquid assets are traded with less frequency and typically due to valuation reasons. Such different trading motives by themselves should not have any differential impact on the volatility or risk of the price of these assets as long as agents' wealth shocks cancel each other out on in the aggregate.

Yet, it has been empirically and theoretically shown that there exists a linkage between market events and agents' funding liquidity[1]. A systematic link between the market and funding liquidity can lead to correlated wealth shocks and hence correlated trading behavior of agents. It has been shown by Hasbrouck and Seppi (2001) that correlated order flows cause commonality in variation of asset prices. Hence, I argue that if systematic market events create wealth- (funding liquidity) shocks, which in turn lead to correlated liquidity trading, this leads to price pressure and hence and increase in systematic price risk of assets with respect to the market risk factor beyond the underlying risk from asset fundamentals.

As liquidity driven trading is concentrated on liquid assets, since they can be traded less costly, this means that liquid asset prices become relatively more correlated with any systematic trading factor than illiquid assets. In this chapter I study the link between price risk and asymmetric trading cost, i.e. differences in beta risk in the cross-section of liquid and illiquid assets. In particular, I investigate if differences in systematic risk of liquid and illiquid asset returns exist and whether they diminish when trading costs are reduced. Especially for valuation and any applications where the true risk asset risk of a firm is inferred by de-leveraging stock-price-betas it is important to first adjust for the asymmetry caused by differences in liquidity in the cross-section.

In the theoretical part of this article I present a model of portfolio choice with wealth-constrained agents subject to stochastic wealth shocks holding portfolios of liquid and illiquid assets. I hypothesize that correlated wealth shocks can significantly increase the systematic price risk of liquid assets beyond the level of risk from their underlying dividend process. At the same time, by way of construction of the market risk factor, illiquid asset risk becomes underestimated. I further hypothesize that a uniform reduction in trading cost should lead to a convergence in the level

[1]See: Brunnermeier and Pedersen (2005), Borio (2004), etc.

of systematic risk between illiquid assets and liquid assets, since agents start to diversify some of their liquidity trading activity away from the more liquid asset class.

Empirical evidence is presented supporting these two hypotheses. I find significant differences in market risk beta coefficients in the liquidity cross-section of US stocks. As a natural experiment for trading cost reduction I use the reduction of the tick size at the NYSE. Since it is an exogenous event, orthogonal to asset betas, it can be used to estimate the impact of a reduction in trading cost onto risk factor coefficients of asset portfolios with different levels of liquidity. From CRSP data I construct 5 such liquidity-sorted portfolios of US stocks and estimate their Fama-French factor loadings before and after the reduction of the tick. I find that market risk of illiquid portfolios increases disproportionally, significantly and persistently after the event compared to liquid assets. Furthermore, illiquid portfolios become more correlated with the size factor, which is evidence that smaller stocks are being more actively traded due to investors diversifying their liquidity trading portfolio. As control group I use a matching set of portfolios of stocks traded on AMEX and NASDAQ, where there was no reduction in tick size, and I do not observe any change in risk for assets with similar liquidity characteristics. Finally, I show that trading volume and volatility in daily trading volume increase for the less liquid portfolios at the NYSE, which can be seen as further evidence supporting the idea presented in this research.

This chapter is structured as follows: Section 2.2 reviews related theoretical literature, while Section 2.3 describes the theoretical motivation. The empirical methodology is illustrated in Section 2.4, and Section 2.5 contains the results of the empirical analysis. Finally, Section 2.6 concludes.

2.2 Related literature

The first related branch of market liquidity literature investigates how liquidity as specific asset characteristic should be priced. Closely related to this chapter is the seminal paper by Amihud and Mendelson (1986), as I use a modified version of their model as point of departure. Amihud and Mendelson introduce a standard model with exogenous, constant transaction costs. Investors are heterogeneous in their expected trading horizon. In equilibrium long horizon traders hold illiquid assets, short horizon traders liquid assets and the asset price incorporates the entire expected future stream of transaction costs. Moreover, long horizon traders are able to charge a liquidity premium, which exceeds the actual trading costs. Further work by Acharya and Pedersen (2005), Pastor and Stambaugh (2003) and Jacoby et al. (2000) considers market liquidity risk with stochastic transaction cost. These studies investigate whether average market liquidity is a state variable for asset pricing, which is the foundation of the liquidity-adjusted CAPM Models, which feature up to three liquidity betas in addition to the usual market beta. I do not use a liquidity-adjusted CAPM framework, as in my setup the market factor drives order flow, which in turn influences asset prices systematically. Variations in liquidity risk come directly from the market risk factor, therefore there is no additional exogenous liquidity risk factor.

Second, market liquidity depends on the trading needs of market participants. Huang (2003) describes a model where agents have a stochastic trading horizon and face known (constant) transaction cost. In this model agents hold portfolios of risk-free assets, liquid and illiquid. He uses an OLG setup where investors must liquidate all their holdings at the end of their trading horizon. The stochastic trading horizon makes the returns of the risk-free illiquid asset risky, given that spreading its fixed transaction cost over a stochastic holding period creates uncertain period returns. In equilibrium, investors hold portfolios of liquid and illiquid assets according to their expected trading horizon, while demanding an illiquidity premium that exceeds the expected present value of actual transaction costs. Here, in this chapter, I get a similar portfolio result, as I combine the idea of having stochastic trading needs with the basic structure of Amihud and Mendelson (1986) described earlier.

The third and final branch of related liquidity literature concerns funding liquidity. It investigates how agents' trading needs arise from shocks to their balance sheet. In their seminal paper Brunnermeier and Pedersen (2006) describe a model which links market liquidity to the funding liquidity of financial intermediaries. They show that there is a mutually reinforcing mechanism, which eventually leads to "flight to liquidity" during high margin times (in their model considered as "crisis"). Similarly, Vayanos (2004) proposes a "dynamic model with investors being fund managers, subject to withdrawals when fund performance falls below a threshold". He shows that, in equilibrium, managers will hold portfolios of liquid and illiquid assets according to their expected liquidity needs. Vayanos (2004) links fund performance to dividend volatility. Fund managers thus expect higher liquidity needs during more volatile times. In the study he demonstrates that liquidity premia increase with volatility, as higher volatility increases demand for liquidity and depresses illiquid asset prices. Acharya and Schaefer (2006) argue that capital and collateral requirements for trading of assets introduce a link between market and funding liquidity of financial intermediaries. They conject that financial intermediation can actually increase liquidity risk in financial markets. Additional papers investigating strategic trading due to liquidity constraints are Brunnermeier and Pedersen (2005), Morris and Shin (2004) and Bernardo and Welch (2004). The theoretical study by Morris and Shin (2004) shows how market liquidity spirals or liquidity "black holes" can emerge from strategic trading that stems from constraints in funding liquidity. Similarly, Bernardo and Welch (2004) model a run on the financial market (similar to Diamond and Dybvig (1983) type runs on institutions). These models are just a few of many that describe the mutually reinforcing relationship between funding liquidity and the market. Given this body of literature I implicitly assume that a link between market events and funding shocks exists and leads to correlated trading needs between agents, and therefore do not model it explicitly.

Empirically related are Sun (2007), who finds that mutual funds with the same clientele suffer correlated liquidity shocks. These shocks generate correlated order flows from funds in the underlying stocks and lead to co-movement in returns and liquidity of these stocks. Hasbrouck and Seppi (2001) find that commonality in orderflow explain 2/3 of commonality in returns.

2.3 Theoretical Motivation

This setup borrows many aspects of the model of Amihud and Mendelson (1986), who solve an asset-pricing problem for a universe of assets with different, but exogenously fixed, trading costs. They describe an overlapping generation (OLG) setup with a heterogeneous population of risk neutral investors who exogenously differ in their expected trading horizon. In equilibrium investors in Amihud and Mendelson (1986) hold assets matching their expected trading horizon, long horizon traders holding illiquid assets and short horizon traders holding liquid assets. As they are risk neutral, there is no benefit from diversification and they simply maximize expected return.

Here, let us assume a homogeneous population of risk averse investors or agents, and systematically correlated, liquidity - motivated trading behavior of these agents. Hence, each investor faces stochastic funding shocks with zero mean, and correlation between investors' shocks is positive. I assume investors' liquidity shocks to be correlated with the market risk factor in this economy. Funding shock correlation between agents arises as a result of this. Nevertheless, I do not model this explicitly, but set such correlation as an exogenously given fact. Investors hold and trade diversified portfolios of liquid and illiquid assets matching their expected liquidity needs, similar to the model of Huang (2003). The particular point of interest here is the differential impact of correlated trading patterns on asset prices and risk in the liquidity cross-section.

To formalize, let there exist M investors $m = 1, 2, ..., M$ and $N + 1$ capital assets indexed by $n = 0, 1, 2, ..., N$. Each asset n generates a stochastic dividend stream $d_n = \lambda d_m + \epsilon_n$, where d_m is the dividend stream of the market portfolio and an idiosyncratic component ϵ_n with $E(\epsilon_n) = 0$. Furthermore, each asset $n = 0, ..., N$ has constant relative transaction cost c_n. Each asset has the same $\lambda = 1/(N+1)$ coefficient, leading to a uniform level $\beta = 1$ of systematic risk from the dividend process with respect to the market portfolio for all assets. Capital assets are sorted by their transaction cost, so $c_0 < c_1 < c_2 < ... < c_N$. Assets are perfectly divisible and all assets are in positive unit net supply.

All investors initially have an equal level of wealth and are subject to individual funding shocks s_m $\forall$ $m = 1...M$ with realizations Σ_m in each period. A positive funding shock means that an agent has to buy assets and expand his portfolios, whereas a negative funding shock means that this agent has to sell some of his portfolio holdings. Their shocks are normally distributed, with zero mean, volatility of σ^2 and correlation $\rho = cov(s_i, s_j)/\sigma^2$ $\forall$ $i, j = 1, 2, ..., M$ and $i \neq j$. All agents $m = 1, ..., M$, demand an optimal portfolio of assets described by their demand vector $d_m = \{\omega_{m,0}, \omega_{m,1}, ..., \omega_{m,N}\}$, where the sum of portfolio investments ω adds up to their initial wealth. Agents by themselves are marginal and their demand does not have an impact on the price of an asset.

If trading costs were to be zero (or positive, but equal across assets), each agent would optimally diversify and demand an equal share in each asset. In contrast, in the case of heterogeneous trading cost, portfolio weights become a function of average funding shock volatility, since investors will demand more liquid assets if they expect a higher probability of a large outflow. They will skew their portfolio weights towards liquid assets up to the point where the marginal expected liquidation cost equals marginal cost from diversification benefits. Figure 5 shows a simplified example of portfolio investment of unit value for the different cases without and with differential trading cost at different levels of funding shock volatility[2]. The figure illustrates "flight to liquidity" for the high uncertainty case (high volatility σ^2) with demand moving from illiquid to liquid assets.

When agent m is hit by a negative funding shock of size Σ_m, he sells some of his most liquid holdings first, then some less liquid and so forth until total volume sold equals the size of the funding shock (his current liquidity needs). Figure 6 illustrates the changes in portfolio investment for the different cases of inflows and outflows with and without transaction cost. Each agent rebalances his portfolio to match marginal transaction cost today with marginal expected, risk-adjusted transaction cost tomorrow plus the marginal loss of benefits from non-optimal diversification. Since funding shocks have an expected zero mean, the portfolio allocation line in Figure 6 can be expected to rotate around its initial value. So, if - for example - $\Sigma_m = \omega_{m,0} + \omega_{m,1}$, agent m will sell a large part of his holdings of assets 0 and 1 and some of his holdings of other assets, and ends up with portfolio vector $d'_m = \{\omega'_{m,0}, \omega'_{m,1}, \omega'_{m,2}, \omega'_{m,3}, ..., \omega'_{m,N}\}$, where $\omega_{m,0} - \omega'_{m,0} > \omega_{m,1} - \omega'_{m,1} > \omega_{m,2} - \omega'_{m,2} > ... > \omega_{m,N} - \omega'_{m,N}$ and $(\omega_{m,0} - \omega'_{m,0}) + (\omega_{m,1} - \omega'_{m,1}) + (\omega_{m,2} - \omega'_{m,2}) + ... + (\omega_{m,N} - \omega'_{m,N}) = \Sigma_m$. In case of a positive funding shock, investors scale up their portfolios, first buying the most liquid asset, then the

[2]For simplicity, in the figure I assume linearity in trading-costs and diversification benefits in the asset cross-section.

second most liquid, and so forth.

If we assume - for a moment - that correlation ρ between agents' funding shocks is zero, so all wealth shocks s_i are independently and identically distributed, results are identical to Amihud and Mendelson (1986) and Huang (2003). A risk-premium for holding illiquid assets exists, since risk averse agents tend to tilt their portfolios towards liquid assets to reduce costs from stochastic trading needs. It can easily be seen that the price of an illiquid capital asset drops below the risk-adjusted present value of the underlying systematic dividend process minus the present value of all expected future transaction costs. Aggregate wealth W and the aggregate demand vector $D = \{\Omega_0, \Omega_1, ..., \Omega_N\} = d_1 + d_2 + ... + d_M$ (the sum of all portfolio vectors), which in the case with correlation are stochastically affected by the average aggregate shock, remain constant under the assumption of zero funding shock correlation since agents' funding shocks cancel out. The average aggregate shock is defined by $S = (s_1 + s_2 + ... + s_M)/M$ with realization $\Sigma = (\Sigma_1 + \Sigma_2 + ... + \Sigma_M)/M$, $E(S) = 0$ and $Var(S) = \sigma^2/M$, so by law of large numbers $\lim_{M\to\infty}(Var(S)) = \lim_{M\to\infty}(\sigma^2/M) = 0$.

If instead we assume agents' funding shocks to be positively correlated with the systematic factor in this economy, aggregate wealth will also fluctuate systematically. The aggregate average shock S still has an expected value of $E(S) = 0$ but variance becomes positive, since $Var(S) = \sigma^2/M + \sigma^2\rho(M-1)/M$, so $\lim_{M\to\infty}(Var(S)) = \sigma^2\rho > 0$. This means that now there is a probability of non-zero realizations Σ of the aggregate shock S. Since asset supply is fixed, an aggregate wealth shock leads to a proportional price change in the market portfolio. If d_m is to represent the risk factor in this setup and we assume that there exists positive correlation of the market dividend process with individual wealth shocks (and hence with the aggregate shock), then the price of the market portfolio will move in excess of the variations driven purely by the dividend process.

As was shown in Figure 6, after being hit by a wealth shock agents trade liquid assets rather than costly illiquid assets when rebalancing. In the earlier case of zero correlation, individual shocks cancelled out and aggregate asset demand remained constant with demand for liquid assets exceeding illiquid asset demand, and therefore illiquid assets were being priced at a discount. In the case of positive correlation between shocks, the aggregate shock becomes stochastic with non-zero realizations[3] and aggregate demand fluctuates. The aggregate demand vector rotates around its mean similar to the rebalancing of individual portfolio demand depicted in Figure 6. In the case of a negative realization Σ of the aggregate shock S investors sell the more liquid part of their portfolios which leads to a relative reduction in the price of liquid assets[4]. The opposite holds for positive realizations of S. Since the aggregate shock S is positively correlated to the market risk factor d_m this leads to an increase in correlation between the market return and liquid-asset returns from liquidity driven trading. Two forces drive this increase in correlation. First, market return is partially driven by the aggregate shock and second, by the systematic component in the shock itself. This has a number of implications for estimating the systematic risk of assets using the CAPM model.

Hypothesis 1: *The β_{CAPM} coefficient of systematic risk for liquid assets exceeds the true β systematic risk of the underlying dividend process, while β_{CAPM} of illiquid assets underestimates*

[3]The expected aggregate shock remains equal to zero, but variance becomes positive.

[4]It has to be pointed out that such liquidity induced price effects can only be observed when assuming that agents are (at least partially) borrowing constrained and that there is no outside liquidity provider. If such a liquidity provider existed, he would immediately act upon the arbitrage opportunity from mis-priced assets, inject capital into the market and restore asset prices to their intrinsic values. The more constrained aggregate wealth becomes, the higher is the reward a liquidity provider would receive.

the true underlying systematic risk.

As was shown above, the systematic price risk of liquid assets increases above the level of risk from the underlying dividend process. This relative increase in the β_{CAPM} coefficient of the liquid asset class automatically leads to a relative decrease in realized β_{CAPM} for illiquid assets, since by definition the β_{CAPM} coefficient of the market portfolio must remain equal to 1.

Hypothesis 2: *A uniform reduction of trading cost in the cross-section leads to a reduction of the β_{CAPM} coefficient of systematic risk for liquid assets towards the level of systematic risk β of the underlying dividend process, and, vice-versa, an increase in β_{CAPM} for illiquid assets.*

If trading costs are reduced uniformly in the cross section, marginal benefits of diversification will exceed marginal trading cost. Hence, investors reallocate their funds to hold more diversified portfolios that are less skewed towards liquid assets. Therefore, illiquid assets will be traded relatively more and liquid assets less when accommodating liquidity shocks. This means that the observed CAPM coefficient for illiquid assets increases while it decreases for liquid assets.

The average expectation agents have about the variance of their individual wealth shocks drives the flight to liquidity effect. Holding all else equal, an increase in variance leads to higher demand for liquid assets and therefore a lower return, while increasing the liquidity premium for illiquid assets. An increase in correlation between shocks does not increase the liquidity premium. Nevertheless, a hike in correlation will increase the relative difference in observed β_{CAPM} risk between liquid and illiquid assets. In the limit, when wealth shock correlation goes to zero the difference in β_{CAPM} risk between assets also goes to zero. Finally, without asymmetric trading cost β_{CAPM} becomes equal to

1 for all assets, as they are considered equally risky with respect to their underlying dividend process.

The pricing risk described here is similar to risk captured by liquidity risk factor in a liquidity-adjusted CAPM Model, yet there are a number of important differences. First, and foremost, the model presented in this paper does not contain an exogenous liquidity risk factor. The state variable used is correlation between individual liquidity shocks and the market risk factor, which forces correlation between individual shocks, and therefore variation in the aggregate shock. So, additional price-risk arises from an amplification of the risk from the market-factor and should therefore be considered systematic market risk and not liquidity risk. This extra risk is then distributed unevenly due to the differences of liquidity characteristics in the liquidity cross-section of assets. An additional liquidity risk factor, such as to build a liquidity adjusted CAPM, can be constructed using a factor-mimicking portfolio orthogonal to market risk, which captures the risk of changes in liquidity unrelated to the market factor. By definition, such a factor would not pick up the effect described in this paper. The important points shown here are that, first, systematic market risk is inflated beyond the level of risk from the underlying dividend process, due to the feedback between market returns and trading needs, and second, this risk varies in the liquidity cross-section of assets.

2.4 Methodology

In the empirical part of this study I test the two hypotheses described in the previous section. First, whether there is a difference in systematic risk (β_{CAPM}) between liquid and illiquid asset portfolios and second, if an exogenous reduction in trading cost leads to a convergence in beta risk between liquid and illiquid assets. I use a 3 factor Fama-French model to measure systematic risk factors. To test for difference in systematic risk for different liquidity classes I sort assets traded at the NYSE, AMEX and NASDAQ into 5 equally weighted portfolios by their Amihud Illiquidity measure. Next, I construct zero cost portfolios using the most and least liquid assets and estimate the 3 Fama-French factor loads. I expect to find a significantly positive market beta for the zero cost portfolio, and a negative size factor. This would mean that liquid assets are significantly more risky with respect to the market factor than illiquid assets. The negative size factor is to be expected due to the fact that the illiquid short-portfolio is expected to have a high positive size factor load.

Second, I estimate the variation in the market beta for a reduction in trading cost. The reduction of the size of the minimum price variation (tick) in quotations at the NYSE is an event where trading cost reduction can be considered exogenous and orthogonal to other market events. It has been shown empirically by, for example, Goldstein and Kavajecz (2000) or Chakravarty, Wood and VanNess (2004) that the reduction of the tick at the NYSE has lead to a permanent decrease in the Bid-Ask spread of most assets traded at the exchange. To test for the change in systematic risk, I estimate the Fama-French risk factors for the previously mentioned zero cost portfolios before and after the tick size reduction event and compare the differences with the control group of assets traded at the AMEX and NASDAQ[5]. I test for a significant decrease in the beta coefficient of the market factor for the zero cost portfolio at NYSE in comparison to the control group at AMEX and NASDAQ. Additionally, I test for changes in trading volume and volatility of trading volume for the different liquidity portfolios of assets traded at the NYSE.

Events

The New York Stock Exchange (NYSE) has historically quoted all stock prices in multiples of 1/8$. Quoting prices using such a

[5]The AMEX and NASDAQ exchanges did not simultaneously reduce their tick size with the NYSE.

multiple leads to discrete price-jumps called the *minimum price variation* or *Tick*. The size of the tick at the NYSE has been changed twice during its history. First, the tick was reduced from 1/8$ to 1/16$ on June 24^{th} 1997 and finally from 1/16$ to 1 cent on January 29^{th} 2001. I use the second of these two tick-size reduction events in this study.

A number of papers discuss the various issues surrounding the reduction of the size of the minimum price variation, whether it reduces trading costs and its resulting effect on liquidity. Harris (1997) and Grossman and Miller (1988) argue theoretically that, while a reduction of the minimum price variation certainly decreases the Bid-Ask spread and therefore benefits liquidity demanders, it also decreases profits for liquidity providers due to the reduced spread. It therefore reduces their willingness of providing liquidity to the market, which decreases market depth. Goldstein and Kavajecz (2000) empirically study the impact of the first NYSE tick reduction (Event 1) on Bid-Ask spreads and market depth. They find that the average spread has declined by 0.03$ or 14.3%. Furthermore, they show that cumulative market depth has declined by an average of 48%. The empirical study of Chakravarty et al. (2004) investigates the effects of decimalization at the NYSE (Event 2). Using the decimal pilot project of the NYSE and a matched non-decimal control sample they also estimate the impact of tick reduction on trading costs and depth. They find a significant reduction in average spread between 19% and 30% depending on stock trading volume. Furthermore, they show a significant decline in market depth as well. I argue that regarding market depth there are two forces at work. The decline in liquidity due to reduction of profits as outlined above, and second, a shift in volume traded by noise trades from liquid to illiquid assets as described in the theoretical section of this chapter. The empirical evidence found by Goldstein and Kavajecz (2000) and Chakravarty et al. (2004) supports the first effect, while in this study I investigate the second. To support my idea, I am testing for changes in the average trading volume in the liquidity cross-section of assets as well as for changes in risk factor coefficients.

The discussions in Harris (1997), Goldstein and Kavajecz (2000) and Chakravarty et al. (2004) hint towards the fact that a reduction of the Bid-Ask spread should only occur for assets for which the tick had been binding the spread, this means only if the real spread was smaller than the minimum tick prior to reduction. So, for example, if the real spread of a particular stock is 3 cents, yet prior to the tick reduction from 1/8$ (12.5 cent) to 1/16$ (6.25 cent) this spread would have been quoted at 12.5 cents. After the reduction it would be quoted at the smaller tick of 6.25 cents. The argument goes that if the real Bid-Ask spread is larger than the minimum tick size there should not be a decrease in spread if the tick is reduced. This would mean that only relatively liquid stocks, with small Bid-Ask spreads, should exhibit a reduction in trading costs. I disagree, and argue that all spreads should exhibit a reduction, regardless of initial size. For example, a stock with a real spread of 15 cents (which is larger than the 1/8$ minimum tick) will be quoted at 25 cents (two times the minimum 1/8$ tick) before the reduction and at 18.75 cents after the reduction (three times the new minimum 1/16$ tick). Hence, such a non-binding spread would have been reduced by 6.25 cents. See Figure 7 for illustration. Market makers will always quote the spread at the next larger possible price point, and never below since they would make a sure loss. I therefore argue that it is prudent to use the tick reduction event in this study, as illiquid stocks with high spreads should also exhibit a reduction in trading cost once the tick size is reduced. Additionally, I test for reduction of the average Bid-Ask and delete assets from the sample that do not exhibit a reduction in their average spread after the respective tick-change event at 95% confidence.

Sample

From the CRSP Common Stock Holdings database I construct two sets of 5 liquidity-sorted portfolios around each of the two tick change events. The first set includes all NYSE traded stocks with price above 1$ that are traded for the entire length of the event window, while the other set contains the control group which consists of stocks traded at the NASDAQ and AMEX. I decided to choose an event window size of 400 trading days (200 days before and after the event). While results are not driven by the window size, I chose a relatively large window to avoid possible criticism regarding the persistency of changes in stocks' beta coefficient. The estimation window spans April 13^{th} 2000 to November 16^{th} 2001. Low-price stocks are removed to avoid estimation noise from the minimum tick[6]. Stocks with more than one share class are treated as multiple assets. I estimate the average Bid-Ask spread for each asset before and after the event and exclude all assets from the sample where a significant decrease in the average spread size can not be observed with 95% confidence. After filtration there are 1530 NYSE stocks in the sample.

Finally, I estimate the average $ILLIQ$ measure of Amihud (2002) for each stock using the average ratio of absolute daily return to daily dollar trading volume,

$$ILLIQ_i = \frac{1}{D}\sum_{t=1}^{D_i}\frac{|r_{i,d}|}{VOLD_{i,d}}$$

where $r_{i,d}$ is the return of asset i on day d, $VOLD_{i,d}$ denotes the corresponding dollar trading volume and D_i the number of trading days of asset i. Amihud shows that $ILLIQ$ is strongly and positively related to microstructure estimates of actual illiquid-

[6]Some previous studies use a 5$ cutoff at a minimum tick of 1/8$ or larger. I decided instead to apply a lower 1$ cutoff price. Moreover, the sample period in this study has a 1/16$ minimum tick or smaller. Nevertheless, results are robust to an increase of the cutoff price. See Harris (1994) for an in-depth discussion.

ity. The higher the value of the $ILLIQ$ measure, the more illiquid is the particular stock. The measure is then used to construct the two sets of liquidity sorted, equally weighted, buy-and-hold quintile portfolios.

Estimators

As described above, I estimate difference in difference coefficients of the beta risk factors of each treatment/control group portfolio-pair before and after each respective event with respect to Fama-French size and value factors in addition to the market factor. The regressions contain two dummy variables, D_1 which is set to zero for the 200 days before the event and to 1 for the period after, and D_2 which is set to zero for the control group, as well as an interaction term for the difference in difference estimation.

To address asynchronous trading issues in estimations using daily data and illiquid assets I employ the 3-day estimator of Scholes and Williams (1977),

$$\hat{\beta}_{3day} = \frac{\hat{\beta}^{+}_{OLS} + \hat{\beta}_{OLS} + \hat{\beta}^{-}_{OLS}}{1 + 2\hat{\rho}_{factor}}$$

where the 3-day estimator is calculated by adding one-day-lead and one-day-lag returns and averaging their estimated coefficients by dividing by the estimated first-order autocorrelation of the respective risk factor. I am estimating standard errors of the Scholes-Williams $\hat{\beta}_{3day}$ coefficient via bootstrap.

2.5 Empirical Results

Table A.9 in the Appendix shows the average spread of each portfolio as a percentage of its mid-price. It can be observed that the average spread increases in illiquidity. The second row shows the reduction in spread size after the tick-reduction event. The average spread reduces more for illiquid assets with average trading cost of the most illiquid portfolio reducing by as much as -1.66%

of asset mid-price, whereas the most liquid portfolio shows a reduction of only -0.37%. Table A.9 also provides the average of the Amihud illiquidity measure for each of the 5 liquidity portfolios.

In Table A.10, I report measured changes in daily trading volume before and after the second tick reduction event for the 5 NYSE liquidity-sorted portfolios. As described in the theoretical motivation, the main factor that can drive a change in systematic risk with a uniform reduction in trading cost is a shift in trading volume from liquid to illiquid assets due to diversification, which in turn increases correlated trading activity of illiquid stocks. Therefore, a relative increase of daily trading volume for the less liquid stock portfolios should be expected. First, I calculate the trading volume for each portfolio and estimate the mean of this daily portfolio volume before and after the tick reduction. Second, a t-test shows that the average daily trading volume significantly increases for portfolios 2-5, while it drops for portfolio 1. Significance levels are below 0.1% for the results of portfolios 1-4 and below 5% for portfolio 5. Next I analyze the second moment of trading volume. If systematic price risk is to increase due to correlated trading activity, then there has to be an observable increase in volatility of trading volume. The lower panel of Table A.10 shows the estimated volatility of trading volume for each of the 5 portfolios. Using an F-test for change of variance I find a significant relative increase in variance of trading volume of 15.8% for the most illiquid portfolio at 5% significance. A statistically significant change in variance for the more liquid portfolios 1-4 can not be observed.

Tables A.11 - A.13 show the regression results for changes in beta for the 5 liquidity sorted portfolios. A.11 reports the difference in difference estimation for the set of long-short zero-cost portfolio pairs, while results for the separate portfolios traded at NYSE and NASDAQ/AMEX are shown in Tables A.12 and A.13

respectively. Consistent with the first hypothesis that beta for liquid assets overestimates true underlying risk, while beta for illiquid assets underestimates such, it can be observed that the market beta for liquid portfolios exceeds market beta for illiquid portfolios in the sample. The first column in Table A.11 shows a significantly positive beta for zero cost portfolios long in liquid and short in illiquid stocks. These findings are in line with Hypothesis 1.

The idea behind the second hypothesis is that a uniform reduction of trading cost in the cross-section should reduce the difference in beta between liquid and illiquid assets. The left columns of Table A.11 show the difference and difference in difference coefficients for changes in portfolio beta of zero cost portfolios long in liquid and short in illiquid stocks after the spread size reduction. It can be seen that the market beta estimate for the portfolio in the NYSE treatment group is significantly reduced, while such a reduction does not occur for the matching control sample portfolio at NASDAQ/AMEX. Tables A.12 and A.13 show the changes in beta for each of the 5 liquidity classes at both exchanges. For portfolios P4-P5 at NYSE I report a statistically significant increase in beta, while P1-P3 do not show significant changes in beta. Furthermore, a change in beta can not be measured for any of the control group portfolios. These findings support the second hypothesis.

The size factor of the zero cost portfolio is -0.56, which means that the illiquid short part of the portfolio has a higher size factor load than the liquid long part, which is in line with expectations. Table A.12 shows monotonically increasing size factor load, from -0.11 for P1 up to 0.45 for P5 NYSE liquidity portfolios. After tick reduction the size factor coefficient significantly increases across all NYSE portfolios. There is no significant difference in the level of increase between liquid and illiquid NYSE portfolios. But, the difference in difference estimator for the size factor in Table A.11 is positive and significant, therefore there is a significant increase in size load at the illiquid end at the NYSE compared to the control sample at NASDAQ/AMEX.

The difference in difference coefficient for the value factor reported in Table A.11 is not significantly different from zero, so no difference in relative HML factor load between the NYSE and the control sample at NASDAQ/AMEX can be reported with regard to the tick change event.

Discussion and Implications

The main idea behind this research is that commonality in order flow and asymmetric trading costs concentrates trading activity on a subset of liquid assets in the market, hence leading to an increase in systematic price risk for that subset. To prove this idea, it is supposed that with a uniform reduction of trading cost some of the asymmetry in trading activity is reduced due to increased diversification benefits which would lead to a convergence in the level of systematic price risk between liquid (cheaply traded) and illiquid (costly) asset classes. Empirical evidence is presented supporting the two hypotheses that were derived from this idea.

First, it is found that liquid and illiquid portfolios differ significantly in their level of market risk, which supports the basic assumption that liquid assets are more actively traded in a correlated manner than illiquid assets, hence increasing their systematic price risk. The difference in beta between portfolios is quite large, the most liquid at 0.96, with monotonically decreasing values towards the least liquid, which is estimated at 0.48. It has to be noted that, while these are quite well diversified portfolios, they differ very significantly in market capitalization and trading volume. The most illiquid portfolio P5 represents stocks with a daily trading volume amounting to only around 0.5% of that of the most liquid portfolio P1. Moreover, portfolios are calculated equally weighted, rather than value weighted like the market portfolio, which adds to the skewness in beta estimates. Next, it is worth pointing out the fact that the adjusted R^2 reported in Table A.12 decreases monotonically with illiquidity. It seems therefore a the standard 3-factor model has less explanatory power for the returns of illiquid portfolios than for liquid portfolio returns. I would like to argue that this is not so much due to a missing, "unknown" risk factor, but more due to the fact that the market risk factor itself contains both, the risk from the underlying dividend process of stocks, as well as the price risk that stems from commonality in order flows. Since I propose that liquid assets are traded for liquidity reasons as well as valuation reasons, a 3-factor model containing the market risk factor must therefore have a higher degree of explanatory power for returns of liquid assets than for illiquid assets, which are less commonly traded.[7]

Second, evidence is found for convergence in beta between liquid and illiquid portfolios after reduction in trading cost. This convergence is driven by a significant increase in the market risk factor coefficient of illiquid portfolios. Even though from theory a reduction in beta for the most liquid P1 could also have been predicted, yet, as this portfolio basically represents a large part of the capitalization of the market portfolio itself, it is unlikely that a significant drop in beta, which must offset the increase in risk at its comparatively minuscule P4 and P5 counterparts, can be measured. Nevertheless, as I can report a significance decrease in beta for the long-short zero cost portfolio in comparison to its control group pair, this can be interpreted as evidence of beta convergence and therefore supports the idea described in the second hypothesis. Additionally, tests for changes in trading volume show that the most liquid assets are traded less while there is a significant increase in trading volume for illiquid assets after the reduction in trading cost. Moreover, an increase in

[7]In this study I have not included a liquidity factor such as the one proposed by Pastor and Stambaugh (2003), but I would like to do so in future research.

volatility of trading volume can be found for assets in the illiquid portfolio. These findings further support the fundamental idea of this study that a reduction in trading cost asymmetry leads to a redistribution of trading activity and hence a spreading of price risk from correlated trading activity across a larger part of the asset cross-section.

Regarding the other risk factors it appears that the size factor becomes more dominant in illiquid portfolios after the event, which could be seen as evidence that the reduction of trading cost leads to higher trading activity of small company stocks, hence increasing the factor load. In the control group I observe a reduction in the size factor load which could be evidence for portfolio rebalancing of between the two exchanges after it has become cheaper to trade NYSE illiquid assets. No significant results were found regarding changes in the value factor.

These results have strong implications on the use of observed beta as a basis for valuation of assets or estimation of cost of capital. As many business applications require an estimation of cost of capital representing the risk underlying a certain business activity, it is a common practice to estimate the market beta of equity for a similar publicly traded company and to determine the asset beta coefficient by de-leveraging. Using the asset beta, the cost of capital for the assets of a firm can be calculated. This technique requires that the equity beta to asset beta ratio is determined solely from the leverage of the company. Nevertheless, in this paper I show that the liquidity of the stock in the market can move the equity beta away from its "true" value. Ignoring this fact means that a cost of capital estimate for assets of a company with illiquid stocks would be biased downwards, while for a liquid stock company this estimate would be biased upwards. One solution to avoid such bias would be to estimate beta using a portfolio of liquid and illiquid, but otherwise similar companies, if possible.

Robustness

The event used in this study is the tick size reduction from 1/16$ to 1/100$ at the NYSE on January 29^{th} 2001. As the tick was reduced once before, from 1/8$ to 1/16$ on June 24^{th} 1997, I repeated the analysis using this prior event. Similar results regarding differences in portfolio betas between liquid and illiquid portfolios can be observed, where the most liquid NYSE portfolio has a market beta of 1.07 and the least liquid 0.81. Nevertheless, I was unable to obtain significant results regarding changes in beta risk due to the event. I argue that this is due to the fact that the amount of possible price quotation points merely doubled in June 1997, while it was increased more than 6-fold for the January 2001 event. This also is reflected in the size of the bid-ask spread reduction, -0.39%[8] for the least liquid portfolio in 1997 compared to -1.66% for the 2001 event. Hence, as trading costs were not reduced nearly as much, it is prudent to expect to find results with a much lower level of significance. Moreover, results for the 1997 event are not in any way contradicting the analysis presented in this chapter.

Very illiquid stocks are not necessarily traded every day, hence a price update might not occur on a daily basis. This does create certain econometric issues when estimating beta risk coefficients for such stocks using daily data. Scholes and Williams (1977) show that non-synchronous trading can lead to significant estimation bias when using daily returns data and propose a 3-day estimator for correction. Nevertheless, the results of some studies have suffered from non-synchronous trading bias, even while using the 3-day estimator or the similar 5-day estimator of Fowler and Rorke (1983). For example, while Lamoureux and Poon (1987) and Brennan and Copeland (1988) find a post

[8]Reduction in relative spread size quoted as percentage of the mid-price.

stock-split increase in beta of stocks using daily data for estimation, Wiggins (1992) argues that their results suffer from extreme non-synchronous trading bias and shows that there is no significant increase in beta when using a longer estimation period and lower-frequency data. In contrast to these studies, which estimate beta of individual stocks, I am concerned with portfolios, each containing around 300 assets. Asynchronous trading problems can be thought of being much less severe when estimating risk coefficients of illiquid stock portfolios, rather than for individual stocks[9]. In this study I have therefore opted to employ the Scholes-Williams 3-day estimator regardless of the above mentioned critiques. To check for robustness and validity of the bootstrapped standard errors, I have repeated the analysis using standard OLS, obtaining almost identical results.

I am reporting results from a 400-day estimation window, with 200 days before and 200 days after the tick-change event. I decided to use this relatively large window size to avoid possible criticism regarding persistence of post-event beta changes. Nevertheless, reducing the window size by one half does not change results in a significant manner.

2.6 Conclusion

The question studied in this chapter is whether or not beta risk coefficients represent the true risk of the underlying asset dividend process with regard to the market risk factor in the presence of correlated liquidity shocks and asymmetric trading costs in the asset cross-section.

Theoretical and empirical evidence is presented supporting the existence of a relationship between the level of systematic price risk of assets and their liquidity characteristics when there

[9] I am assuming that asynchronous trading does not occur in a systematic manner.

is funding-liquidity-driven commonality in order flows in the market. The main idea is that the presence of asymmetric trading costs leads to a concentration of trading activity on a subset of liquid assets in the market. Assuming the existence of a systematic component in funding liquidity that can cause correlation of order-flow with the market risk factor this leads to an increase in systematic price risk for liquid assets. Meanwhile, the estimate of the beta risk coefficient of illiquid assets understates the true level of risk from the underlying dividend process with regard to the market factor. I further argue that with a uniform reduction of trading cost some of the asymmetry in trading activity can be reduced as it increases diversification benefits which lead to a convergence in the level of systematic price risk between liquid (cheaply traded) and illiquid (costly) asset classes.

I find empirical evidence supporting this idea. Differences in beta between liquid and illiquid assets as well as a convergence of risk estimates after an exogenous reduction in trading cost are estimated with statistical significance. Additionally, I find evidence that after trading cost reduction agents reallocate some trading volume to less liquid assets, while simultaneously increasing volatility of volume, which further supports the theoretical idea presented in this paper.

This result is important for a number of reasons. First, it provides evidence that the market risk factor in itself is not only representing the underlying asset risk, but that it also contains a sizable liquidity risk component. Second, estimates of market beta risk coefficients for liquid assets overstate the true risk from the underlying, while vice-versa understating risk of the illiquid asset class. And finally, that a reduction in trading cost or increase in liquidity can reduce such differences and bring beta estimates closer to representing the true value of underlying asset risk relative to the market risk factor, even with the existence of trading flow correlation.

3 Liquidity around Fire Sales

3.1 Introduction

When an investor has an urgent need for liquidity and must sell a large block of a financial asset because of it, it is profitable for other agents to provide liquidity at and to purchase such an asset at a discount. The price in the market gets temporarily pushed below the intrinsic asset value at the time of the transaction and then reverses to the pre-sale level. The buyer of the asset realizes a positive abnormal return during the reversal, which compensates him for providing liquidity at the point of the purchase. On the other hand, the seller incurs a cost from selling the asset at a discount. If the liquidity-motivated sale is large and predictable, there also exists a profitable strategy of front-running the sale by short-selling the asset prior to the liquidity-driven sale[1]. When such liquidity-driven sales are very large and lead to significant downward price-pressure in the market, they are referred to as "fire-sales".

A sale that is known to occur due to funding-liquidity reasons does not convey any new information about the asset to the market, and the asset price as well as asset-liquidity should return to their pre-sale level once the transaction is completed. On the other hand, a sale that takes place due to valuation reasons conveys an unfavorable opinion about the asset to the market, the asset becomes less attractive, which decreases its level of liquidity as other investors may decide to sell due to updated beliefs[2], and the asset price adjusts downward. As no return reversal occurs in the second case, buyers are not compensated for liquidity provision. Market beliefs about the underlying reason for a large sale therefore must be deemed important.

[1]Such a "Predatory Trading" strategy has first been described in Brunnermeier and Pedersen (2006).

[2]If they consider the seller to be sufficiently informed about the true value of the asset.

In general, the liquidity needs of an investor are neither observable, nor predictable, which rules out front-running, and makes liquidity provision risky if the buyer does not know the underlying motive of the sale. Nevertheless, this is not the case for mutual funds, as flows in-and-out of funds are observable by any market participant, and because of their statistical properties, flows are largely predictable. Additionally, the resulting trades made by mutual funds can be very large and can generate significant price movements in the market.

Previous literature, in particular Coval and Stafford (2007) and Chen, Hanson, Hong and Stein (2008), documents evidence of profitable front-running before large mutual fund-sales, but fails to show significant evidence for post-sale liquidity provision. Additionally, return reversals after liquidity driven sales have previously be found to be slow and only partial. Liquidity-provision strategies have not been found to yield significant positive abnormal returns. A possible reason for the absence of liquidity provision could be that the underlying reason for trades is not observable by other market participants, or that ambiguous beliefs are formed about these trades. Additionally, a fire sale might lead to a permanent drop in asset-liquidity if a liquid asset, which becomes temporarily illiquid due to the fire-sale remains illiquid afterwards as market participants shift their liquidity trading towards other liquid assets.

In order to analyze liquidity around fire-sales, I construct and compare samples of three different types of large mutual fund trades. In particular I compare, purely liquidity driven transactions that should not contain information about changes in value beliefs by the fund manager regarding the asset, ambiguous transactions which are liquidity driven, but also signal a change in value beliefs, and sales due to valuation reasons that lack a liquidity component. I do not only compare abnormal returns but also asset-liquidity itself, which, to my knowledge has not been done in previous studies. Doing so allows to document for liquidity provision and investigate if there is a permanent drop in asset-liquidity.

In order to create the three samples I study portfolio choice of mutual funds and present a new methodology for disentangling the information contained in mutual fund trades and flows. I present a series of important findings. First, return reversal in my sample occurs more rapid than shown in previous studies, yet I do not find evidence for a full reversal. Second, I find evidence for a drop in asset liquidity before each mutual fund sale, yet for liquidity driven sales I do not find evidence of a permanent drop in liquidity after the sale event. On the contrary, I find evidence for a permanent increase in illiquidity for value driven sales. Third, I find evidence that asset returns within the sample of liquidity-motivated sales are significantly and positively correlated to the short-term reversal factor of Fama-French, while this is not the case in the other two samples. Finally, I find significant abnormal returns for a strategy of short-term liquidity provision after a fire sale and show that it is possible to construct zero cost portfolios with significantly positive alphas long on liquidity provision and short on valuation sales.

The evidence I present here leads me to conclude that it is in fact possible for market participants to infer the trading motive behind large mutual fund trades and that liquidity provision after fire-sales is a profitable and actively traded strategy.

3.2 Portfolio Liquidity of Mutual Fund Trades

Mutual Funds empirically exhibit strong first-order autocorrelation in their flows[3]. In this section I argue that this property influences mutual fund managers' portfolio choice with regard to liquidity of the portfolio and their choice of trading portfolios.

When liquidity needs are not autocorrelated, it is optimal for investors to sell the more liquid part of their portfolio first when hit by a negative wealth shock in order to minimize trading cost. Choosing to sell the more liquid part of the portfolio automatically makes the remaining portfolio less liquid and leads to a fluctuation of overall portfolio weights around their optimal values over time, with respect to the portfolios liquidity. So, investors temporarily hold portfolios with non-optimal weights, over- or underweighting certain assets. But, since wealth shocks are stochastically independent from one period to the next, expected portfolio weights are equal to the optimal weights. Trading portfolios, which consist of the assets traded to absorb shocks, contain assets that are more liquid than the assets in the remaining part of the portfolio in order to minimize current period trading cost.

By contrast, in the case of mutual funds, where funding shocks are very highly auto-correlated, it is not optimal for a fund manager to first sell a more liquid portfolio, since in the next period less liquid assets would have to be sold anyways, and the portfolio would tilt away too far from being optimally diversified. In case of anticipated negative shocks, the ex-ante optimal portfolio is more liquid, reflecting the trade-off between trading costs and diversification benefits. The corresponding trading portfolios have the same portfolio weights as the optimal ex-ante portfolio, leading to portfolio scaling, which keeps weights constant and at

[3] See for example: Warther (1995)

the optimal level at all times. This is in line with empirically observed facts, such as funds holding more liquid portfolios when anticipating higher flows and that mutual funds scale their portfolio positions up and down to a large degree with inflows and redemptions. Huang (2012) finds that mutual funds hold more liquid portfolios on average during times of high market volatility, where they expect larger flows. Lou (2010) finds evidence of mutual funds scaling their portfolios almost perfectly, with a scaling factor of 0.97 for outflows and 0.63 for inflows, which means that their trading portfolios have the same portfolio weights as their ex-ante portfolios.

3.3 Mutual Fund Flows and Fire-Sales

Since mutual fund flows are observable and largely predictable, trades made by a fund manager convey a lot of information about a fund's expectations regarding the traded asset, depending on the fund's contemporaneous capital flow relative to the direction of the respective trade. In this section I discuss which information can and cannot be inferred from mutual fund trades and flows, and I build a methodological framework for evaluating information contained in trades by the mutual fund sector.

Mutual funds are restricted from short-selling or borrowing and they typically invest most of their moneys into long, diversified equity portfolios, while holding rather small cash positions. This implies that a fund has to liquidate some of its investment portfolio when experiencing outflows, even for small redemptions by its fund investors. Conversely, since holding large cash positions for too long deteriorates fund performance, a fund tends to expand its equity portfolio rather quickly when receiving an inflow of capital. When redemptions are very large, the resulting trades are considered fire-sales, since the fund is required react to the flow and must liquidate a large equity position at once and typically at a large discount. Such trades present problems, since a large part of mutual fund flows is predictable by any market participant. For example, a hedge-fund may decide to play a strategy where it front-runs expected mutual fund fire-sales by short-selling assets held by funds that are likely to experience large outflows. The mutual fund on the other hand cannot react ex-ante to its own expected flows, since it is typically prohibited to short-sell assets, and is only able to increase its cash buffer up to a certain size in anticipation of an outflow without deteriorating its own performance too much.

When liquidating or expanding its equity portfolio a mutual fund can either keep portfolio weights constant, and simply scale its portfolio up or down, or rebalance by buying or selling a disproportionally large fraction of a particular asset. Such trades and changes in portfolio weights convey information about the fund managers opinion about a particular stock.

Table 3.1: **Mutual Fund Trades and Flows**
The table shows the information conveyed by mutual fund trades conditional on mutual fund flows.

	Mutual Fund Capital Flows		
Transaction	Inflow of Capital	No Flow	Outflow of Capital
Buying	Liquidity or Value Buying	Value-motivated Buying	Value-motivated Buying
Holding	Value-motivated decrease in relative weight	Holding	Value-motivated increase in relative weight
Selling	Value-motivated Selling	Value-motivated Selling	Liquidity or Value Selling

Table 3.1 shows a matrix of flows and trades. Scaling of a fund portfolio while holding weights constant falls into the "Inflow - Buying" and "Outflow - Selling" category. As discussed in the previous section, there is some evidence that mutual funds tend to scale up or down their portfolio positions matching flows. Such scaling trades should be considered purely liquidity driven and

must be seen as information neutral. Nevertheless, not all selling activity during outflows can automatically be considered to be liquidity motivated. A fund manager may sell off overvalued assets disproportionally, which should be considered a value-driven trade. Alternatively, assets bought by a fund while the fund experiences outflows can be considered purely value-driven purchases. The same holds for trades while there are no flows (pure portfolio rebalancing), or assets being held during periods of outflows (which increases the relative portfolio weight for the asset). Similarly, assets sold during periods of inflows, held during periods of inflows or sold while there are no flows can be considered inferior investments as far as the fund-manager is concerned.

From the above categorization we can see the dilemma when trying to disentangle liquidity-driven trades from value-driven portfolio rebalancing. Trades that are counter directional to the corresponding contemporaneous flows are clearly trades made purely for valuation reasons. Meanwhile, it is not possible to simply state that selling during outflows or buying at times of inflows is purely liquidity-driven without also considering relative portfolio weights. The following rules are implied:

Liquidity-driven trades *are asset-sales (purchases) with contemporaneous funding capital outflows (inflows) where the post-adjustment portfolio weight* ω_t *is in the interval* $(\omega_t^*, \omega_{(t-1)}]$, *with* $\omega_t^* = (1 - \frac{Flow_t}{TNA_t})\omega_{(t-1)}$ *defining the post-adjustment portfolio weight that would keep the amount of money invested in the asset constant.*

Value-driven trades *are "trades" which increase (decrease) portfolio weights.*

There is an important conceptual difference between the two. Liquidity-driven trades are actual trades where a fund buys or sells assets in order to absorb a funding shock. Value-driven trades can be actual trades, where a fund buys or sells assets for valuation reasons, but similarly, an increase in the relative portfolio weight of an asset should also be considered a value-driven purchase even if the fund does not actually buy any additional unit of the asset in the market. The reason for distinguishing between the two is that liquidity-driven trading can have a temporary price impact on the asset price with a subsequent return reversal. Meanwhile, portfolio rebalancing conveys information about the fund manager's valuation of an asset, even if the asset is actually not traded.[4]

Figures 8 to 11 in the Appendix illustrate the relationship between liquidity trades and changes in the portfolio weight. Figure 8 shows the base case of portfolio rebalancing in the absence of funding flows. For a reduction in portfolio weight $\omega_t < \omega_{(t-1)}$ the corresponding sale is clearly value driven. The case shown in Figure 9 is for a funding outflow of size $Flow$, which, if the fund would simply scale down its portfolio, would result in a liquidity driven sale of the respective asset with trade-size $Flow \times \omega_{(t-1)}$. It can be seen that if ω_t is in the interval $(\omega_t^*, \omega_{(t-1)}]$, the resulting size of the liquidity-driven sale is between $Flow \times \omega_{(t-1)}$ and zero. As a matter of fact, it could be considered a combination of a liquidity driven sale of size $Flow \times \omega_{(t-1)}$, as in the case of simple scaling, and a simultaneous, smaller, value-driven "purchase" partially offsetting the liquidity-driven sale. Nevertheless, the actual residual trade observable in the market comes from the liquidity-driven portion. Alternatively, post-adjustment portfolio weights larger than ω^* such as shown in Figure 10 can be considered as a combination of a liquidity-driven sale of size $Flow \times \omega_{(t-1)}$ and an offsetting value-driven purchase larger than

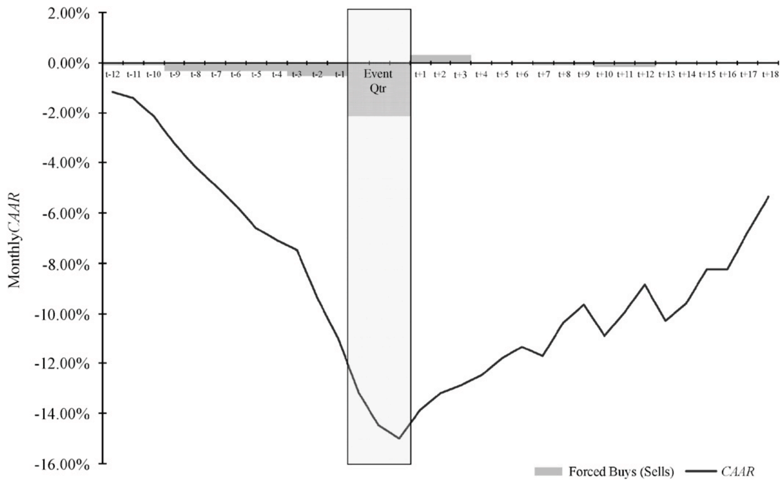
[4]This kind of decomposition, where the deviation in portfolio weight from an index, or in our case, deviation from the previous period portfolio weight, conveys information about the manager's stock picking activity has been documented by Asness (2004), Cremers and Petajisto (2009), Petajisto (2010) and others. Such information about a fund manager's convictions can be used to form trading strategies as is shown in "Best Ideas" by Cohen, Polk and Silli (2010) for example.

the liquidity-driven sale. So, the resulting trade that is observable in the market is the residual portion of the value-driven purchase. So, even small net asset purchases contain a strong valuation statement about the asset if they occur simultaneous to large outflows. Finally, a post-adjustment weight of $\omega_t < \omega_{(t-1)}$, which falls in the area of "liquidity and value-driven trades", such as shown in Figure 11, results in a combination of a liquidity driven sale of size $Flow \times \omega_{(t-1)}$ and an additional value driven sale. The sum of the two is the observable trade in the market. Even though part of the resulting trade should be considered as liquidity-driven, it seems prudent to believe the sale being of a rather value-driven nature, since the fund willingly sells more of the asset than it is required to.

When applying this framework to the analysis of fire-sales, the strongest evidence of flow-driven price pressure with subsequent return reversals should be expected around the scaling point at $\omega_t = \omega_{t-1}$. For assets with post-adjustment weights between scaling and ω^*, the price pressure effect should naturally diminish for weights closer to the point of no trade at ω^*, since the size of the corresponding liquidity-driven trades gets smaller. Return reversal should be expected to be faster for weights closer to ω^*, since these assets must be considered to be undervalued due to the price drop from the fire sale. Similarly, below ω_{t-1} going left towards zero, we can expect to see an increase in the price-pressure effect, but with a decreasing magnitude for the return reversal, since the value-driven motive increases relatively to the liquidity-driven motive of the sale.

It has been documented that there exist profitable trading opportunities around large forced liquidations. In their paper "Predatory Trading" Brunnermeier and Pedersen (2006) describe an optimal strategy as a combination of front-running by selling the asset before the distressed fund sells, and providing liquidity by buying the asset after the fire sale event, in order to reap the

Figure 3.1: **Asset Fire Sales**
This is the original figure published in Coval and Stafford (2007) which shows the results of their event study of cumulative abnormal returns surrounding asset fire sales.



benefits from the return reversal. As far as the ex-ante identification of assets goes, a predatory trader has to be able to identify assets held by distressed funds, that are likely to be sold, which are all assets with a post-adjustment weight below ω^*. If assuming that such a trader can discriminate between assets that are likely to be sold and assets that a fund would buy during a funding outflow, the trader can employ a front-running strategy by short-selling assets likely to be sold. Whether or not these assets are sold for liquidity or valuation reasons does not matter at that point for the implementation of the front-running strategy, since there will be negative price-pressure in the market surrounding the sale of all these assets. Nevertheless, for the post-sale liquidity provision strategy, the trader must be able to distinguish between assets sold for valuation reasons, which are not likely to exhibit a return reversal, and assets sold for liquidity reasons, for which a return reversal can be expected.

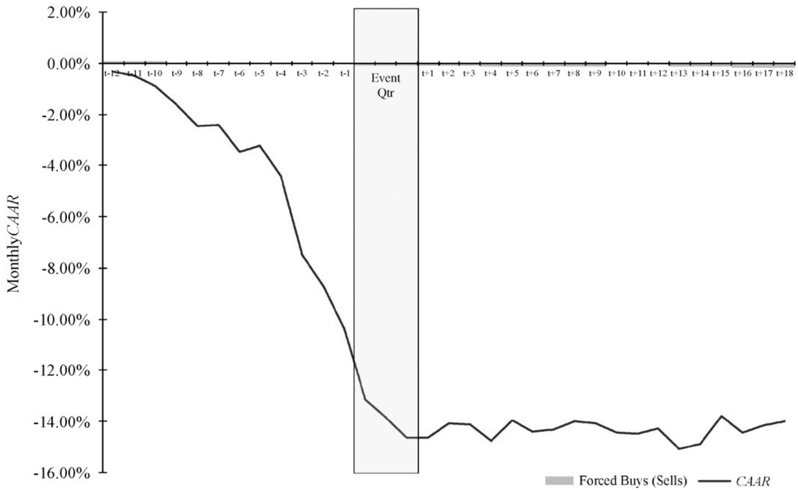
In their seminal paper documenting price pressure and return reversal around fire sale events Coval and Stafford (2007) find evidence of price pressure leading to significant negative abnormal returns in the 12 months before a fire sale and positive abnormal returns after the event leading to a slow, partial return reversal over the 18 months after the event. Coval and Stafford (2007) as well as Chen et al. (2008) interpret this as evidence of hedge-funds actively playing a front-running strategy. Average cumulative abnormal returns in their sample reach around -15% over the 12 months prior to the fire sale quarter. Yet, as far as liquidity provision after the fire-sale event is concerned, both works, Coval and Stafford (2007) and Chen et al. (2008), deem the evidence to be inconclusive. They argue that, due to the length of the return reversal, liquidity provision is not a very profitable strategy. Nevertheless, the focus in Coval and Stafford (2007) is on price pressure and not on liquidity provision and asset-liquidity, so their selection variable for identification of fire sales events is constructed accordingly:

$$PRESSURE\_1_{i,t} = \\ = \frac{\sum_j (max(0,\Delta H_{j,i,t})|flow\%_{j,t}>P(90th)) - \sum_j (max(0,-\Delta H_{j,i,t})|flow\%_{j,t}<P(10th))}{AvgVolume_{i,t-12,t-6}}$$

where, $\Delta H_{j,i,t}$ is the change in holdings of stock i held by fund j during the last period, and, $flow\%_{j,t} = \Delta TNA_{j,t-1,t}/TNA_{j,t}$ represents the fund flow as percentage of total net assets.

Fire sales are identified at the stock level based on the above $PRESSURE\_1$ measure being in the bottom decile of the sample distribution. Using this identification Coval and Stafford (2007) select the mutual funds trades which lead to the highest level of price pressure. Nevertheless, their selection criteria does not include a condition that makes sure that these trades are purely liquidity driven. The trades identified as fire sales by Coval and Stafford (2007) are the top decile of value sold relative to the average volume of the stock and therefore can be sales where a

Figure 3.2: **Unforced Liquidations**
This figure also comes from Coval and Stafford (2007) and shows the results of their event study of cumulative abnormal returns surrounding unforced liquidations.



fund unwinds most of its holdings in a particular asset. When applying the framework described in this chapter, such trades would have post-adjustment weights between zero and ω_{t-1}. The larger, in relative terms, these trades are, the more value motivated they become, as opposed to liquidity-driven, and therefore exhibit more price pressure and less return reversal. It is therefore not surprising that the Coval and Stafford (2007) results show a weak and slow return reversal, as shown in Figure 3.1, and that there is no conclusive evidence to be found about liquidity provision after the fire sale for their sample.

The Coval and Stafford (2007) results for "unforced trades" are shown in Figure 3.2. The assets included in that sub-sample show severe underperformance until the point of sale by the fund, while they stop to underperform once funds unwind their positions. An asset sold for valuation reasons, is likely to have underperformed prior to the sale, but similarly can be expected to underperform after the sale, especially if sold by an institutional, supposedly informed, investor. Yet, from the graph it would appear that mutual fund managers wait for the risk-adjusted asset value to drop to its lowest point before exercising their sale and that the market does not see the mutual fund sale as a signal indicating bad quality. Coval and Stafford (2007) select the trades they consider "unforced" by using the bottom decile of $Unforced\_PRESSURE\_1$:

$$Unforced\_PRESSURE\_1_{i,t} = \frac{\sum_j (max(0, \Delta Holdings_{j,i,t})}{AvgVolume_{i,t-12,t-6}}.$$

This selects the largest sales relative to average volume, unconditional on flows. Unfortunately, with this selection criteria the resulting sample contains an unspecified mix of liquidity-driven (forced) trades and value-driven (unforced) transactions. This can explain the response function displayed in Figure 3.2. While assets that are unwound for valuation reasons may keep underperforming after being sold, the liquidity-driven portion of assets is likely to have some kind of return reversal, hence, adding the two together results in a flat performance plateau after the sale.

In order to distinguish between liquidity-driven and value-driven trades in my empirical analysis I condition a sample of mutual fund trades on changes in the relative post-adjustment portfolio weights of assets.

3.4 Data and Sample Selection

The dataset and filtration methods used in this chapter are similar to Chapter 1. Again, I am using data from the CRSP Survivorship Bias Free Mutual Fund database, the CDA/Spectrum Mutual Fund and Investment Company Common Stock Holdings Database provided by Thompson Reuters, and the CRSP database on common US stocks. The sample period spans January 1990 to December 2008.

From the CRSP Mutual Fund database I use monthly information about funds' total net assets under management (TNA), fund returns, equity ratios and cash holdings for each share-class of the fund. Monthly fund-returns reported in CRSP are net returns, after fees etc., but before any front-end or back-end loads. Following standard literature, I assume implicitly that funds' flows occur at the end of each month, so I calculate monthly flows in and out of funds as:

$$FLOW_{j,t} = TNA_{j,t} - TNA_{j,t-1} * (1 + r_{j,t})$$

where $TNA_{j,t}$ are total net assets held by fund j at time t and fund $j's$ returns $r_{j,t}$ are returns realized in period $[t-1, t]$. I correct for mergers, subtracting the final TNA of the dying fund from the $FLOW$ of the surviving fund during the month of the merger. Since information about merger dates in CRSP is not very precise I have developed a matching procedure to select the month with the highest flow at the acquiring fund as the true month of the merger within a 6-month window $[t-1, t+5]$ around the reported merger date. Additionally, I correct the database for obvious digit entry errors of total net assets by using a procedure to identify subsequent inflows and outflows of the same order but reversed sign due to an outlier in TNA of an order of magnitude of 10 (or 0.1) compared with previous and subsequent TNA values. To avoid removal of correct entries by this procedure I check if the absolute value of the calculated flow created by the erroneous TNA observation is at least 3 standard deviations away from the funds' flow average in order for the erroneous TNA to be removed. The above described procedure and merger correction appear to eliminate almost all of the extreme outliers in the flow distribution. In order to address issues regarding fund incubation bias, I exclude the first 12-month fund returns[5], which also addresses any concerns that new funds might be cross-subsidized

[5] See: Elton et al. (2001) and Evans (2004)

by their respective fund families[6]. I further winsorize the dataset by deleting the 0.1% and 99.9% extreme tails. Finally, I only include funds with minimum TNA of 1M$ in the sample.

The Thompson Reuters' CDA/Spectrum Mutual Fund database contains data on mutual fund portfolio holdings. The reporting frequency is quarterly for most funds in the sample. Since CDA bases its information on the holdings file date, and not the actual reporting date, for which the holdings are valid, I correct stock prices and adjust for eventual stock-splits between reporting and file date. Finally, I merge CRSP and CDA using the MFLINKS tables provided by Wharton Research Data Services (WRDS). As the CDA database reports holdings on fund level, not by fund share class, I consolidate CRSP share classes to fund level, again using the MFLINKS merging table. Fund level returns are calculated as share-class returns value weighted by the TNA of each class, fund level total net assets are the sum of assets of each underlying share-class. To ensure correct mapping I require that the TNA's reported by CRSP and Thompson for each fund do not differ by more that a factor 2 (0.5). I only include US domestic equity mutual funds in the sample with CDA/Spectrum investment objective code specified as aggressive growth, growth, growth and income, balanced, unclassified or missing. Furthermore I restrict the sample to funds with an equity ratio between 0.75 and 1.2 [7].

Data on monthly share prices and returns, bid-ask spreads, volume and shares outstanding is obtained from the CRSP Common Stock Holdings database. I exclude stocks priced below 5$, as is common practice in order to avoid microstructure noise. Furthermore, I use the value weighted market risk factor to calculate betas. Additionally, I calculate point estimates of the Amihud

[6]Gaspar et al. (2006)
[7]See discussion Cremers and Petajisto (2009).

liquidity measure[8] for each stock as $Ami_{i,t} = \frac{|ret_{i,t-1,t}|}{volume_{i,t-1,t}}$.

3.5 Empirical Analysis

In order to analyze if the market is able to infer the trading motive behind large mutual fund trades I construct 3 samples of mutual fund trades. The first sample contains what should be purely liquidity driven trades, the second sample contains trades with both liquidity and value motives and should be considered ambiguous with respect to information. The third includes trades considered to be due to valuation motives rather than liquidity. Next, I analyze asset-liquidity as well as abnormal asset returns around these trades in order to find if there are any differences between these samples which can be seen as evidence that the market is able to correctly infer the trading motive. Finally, I measure the performance of a trading strategy based on the information conveyed in these trades.

Following the methodology outlined in Section 3.3 I construct a sample of liquidity driven mutual fund trades using a measure of flow-induced price pressure as follows:

$$PRESSURE_{i,t}^{forced} = \frac{\sum_j (\Delta Holdings_{i,j,t} | \omega_{i,j,t-1} \leq \omega_{i,j,t} < \omega^*_{i,j})}{AvgVol_{i,t-12,t-6}} \tag{3.1}$$

When conditioning on the post-adjustment portfolio weight of the stock being in the interval $(\omega^*_t, \omega_{(t-1)}]$, with $\omega^*_t = (1 - \frac{Flow_t}{TNA_t})\omega_{(t-1)}$ the actual resulting trade should be considered liquidity driven. The size of the interval $(\omega^*_t, \omega_{(t-1)}]$ itself depends on two factors, namely, mutual fund distress and portfolio concentration. A distressed fund holding a very diversified portfolio will trade less of each individual asset than a similar fund with

[8]See Amihud (2002).

a concentrated portfolio. The price pressure effect will therefore be larger for concentrated fund portfolios. When conditioning on the portfolio weight being in the interval there is no need to simultaneously condition on mutual fund distress. For small flows and diversified portfolios the interval collapses to zero, so any large trades automatically push the portfolio weight out of the interval. Very large changes in holdings, with a portfolio weight within the interval, by definition require very large contemporaneous flows. The larger the changes in holdings, the more the portfolio weight converges to the lagged portfolio weight and the outcome is liquidity-driven scaling. Finally, dividing by the lagged average trading volume of the stock gives a measure of pressure.

I construct event windows around the bottom 1% observations of the pressure variable to capture the largest relative quarterly liquidity-driven sales[9]. In order to have a single flow driven fire sale event in each window I eliminate overlapping event windows from the sample. The reason for only including sales and not purchases in this study is that the immediacy imposed by an outflow has a stronger impact from a liquidity standpoint. Mutual funds with negative flows do not have a choice other than to sell the assets they have in their portfolio, while for inflows, corresponding portfolio-expansion trades can be executed in a more controlled manner.

A single factor market model is used to estimate each stock's long-run beta coefficient using monthly returns. Next, event windows are constructed around each fire sale event. These contain the 12 months of stock returns up until and 18 months after the fire sale event. Using the stock beta estimate I calculate abnormal monthly returns (alpha) in the event window and the corre-

[9]Coval and Stafford (2007) first use the top and bottom decile of flows and then the top decile of pressure, hence 2% of the total sample. Their analysis contains liquidity driven sales and purchases, while in this study I focus on sales.

sponding cumulative abnormal return for each stock. Finally, the equally-weighted average abnormal and cumulative returns are calculated across all event windows. Similarly, I calculate point estimates of the Amihud illiquidity measure for each month of the event window for each stock. Estimates are then normalized within each event window by dividing each subsequent value by the estimated value of the measure for the first month of the respective window. The average monthly values across all event windows are also calculated for the illiquidity measure.

The respective results for cumulative average abnormal returns (CAAR) and illiquidity for liquidity-driven fire-sale trades can be seen in Figures 12 and 13 and in Table A.14. It can be observed that there is significant evidence of front running leading to negative price pressure during the 12 months before the mutual fund sale occurs. For comparison I calculate cumulative abnormal returns for a sample of sales constructed by using a selection criteria similar to Coval and Stafford (2007). The price recovery during the 18 months after the event occurs much faster than shown by Coval and Stafford (2007), but is still far from immediate. Also, it must be noted that return reversal is only partial. As far as liquidity is concerned, it can be observed that assets become relatively illiquid before and until the fire sale, but I do not find statistically significant evidence of a permanent increase in illiquidity after the fire sale event.

Next, I repeat the analysis with a modified specification of pressure in order to capture the "overscaling" effect where mutual funds with outflows disproportionately sell an asset. The trading motive for the trades in this sample is ambiguous, hence the market should not be able to infer the true trading reason behind each trade.

$$PRESSURE_{i,t}^{overscaling} =$$

$$= \frac{\sum_j (\Delta Holdings_{i,j,t} | \omega_{i,j,t} < \omega_{i,j,t-1} AND flow\%_{j,t} < P(10))}{AvgVol_{i,t-12,t-6}} \tag{3.2}$$

Here the sum is conditional on funds reducing the portfolio weight below the level of the lagged weight, so funds are selling more of the particular asset than they would have to by simply scaling down their portfolios. Additionally, relative fund flows have to be in the bottom decile, in order to only include distressed funds with the largest relative outflows. Finally, I am using the bottom decile of this pressure variable to construct fire sales event windows. The results for cumulative abnormal returns and illiquidity can be found in Figures 14 and 15 and in Table A.15. It can be observed that there is a small return reversal after the fire sale event, after which the asset does not continue to underperform. This result is quite similar to the "unforced sales" result of Coval and Stafford (2007) shown in Figure 3.2. As far as asset-liquidity is concerned, I find a statistically significant drop in liquidity prior to the sale, but, I do not find evidence for a permanent increase in illiquidity after the sale, as in the previous case of purely liquidity driven sales.

Finally, I construct a sample containing unforced (voluntary) sales, specified as the largest relative changes in holdings with respect to average volume for the set of mutual funds reducing their portfolio weights in the particular asset with respect to the lagged weight while not being distressed, so having $flow\%_{j,t} > P(10)$, which includes funds with (non-severe) outflows as well as funds with contemporaneous inflows:

$$PRESSURE_{i,t}^{unforced} =$$

$$= \frac{\sum_j (\Delta Holdings_{i,j,t} | \omega_{i,j,t} < \omega_{i,j,t-1} AND flow\%_{j,t} > P(10))}{AvgVol_{i,t-12,t-6}} \tag{3.3}$$

I am using the bottom 1% of this variable in the sample and construct event windows around each of the sales. The results for cumulative abnormal returns and illiquidity for this sample can be found in Figures 16 and 17 and in Table A.16. There appears to be a small return reversal immediately after the event quarter, but it can be seen that cumulative abnormal returns continue to decline afterwards, so the asset keeps underperforming after being sold by the mutual fund sector. This can be seen as evidence for valuation skill of mutual fund managers for large voluntary sales. Due to data availability the event here is specified as a quarter instead of a month. Asset-liquidity drops before the sale, additionally I find statistically significant evidence of increased illiquidity after the sales event.

I obtain similar results when changing the arbitrary cutoff point in the sample-selection, including only sales within the 0.5% and 2% percentiles of the respective pressure statistic. When including more than 2% into the sample, results weaken dramatically which can be attributed to the fact that significant price-pressure in a market as liquid as the US-equity market is only observable for very large transactions. When testing for changes in the Bid-Ask spread instead of the Amihud-measure as an indicator of asset-liquidity, I do not find significant evidence of changes in the average spread around these sales events in any of the 3 samples.

To summarize, a significant return reversal is observable in the short run for liquidity driven sales, while reversals are much smaller for the overscaling and voluntary sales samples. Assets are not significantly less liquid after the sale for the sample of liquidity-driven sales, while there is an observable reduction in post-sale asset-liquidity in the sample of voluntary sales. Both facts combined can be seen as evidence for liquidity provision by outside investors after fire sales, while no liquidity provision strategy is pursued after a value-motivated sale.

In order to provide additional evidence for the presence of a return reversal, in the case of the liquidity-driven sale, I regress the asset returns in excess of the risk-free rate on the short-term reversal factor of Fama-French[10], in addition to the market excess return, size, value and momentum factors within each event window and estimate the mean of the regression coefficients for each sample. Results are shown in Table A.17 in the Appendix. Asset returns in the purely liquidity-motivated sample are shown to be positively and significantly correlated on average with the short term reversal factor, while I do not find such a relationship for the "overscaling" and voluntary sales samples.

Finally, I estimate alphas for trading strategies based on the liquidity-trade and value-trade samples. For every calendar month I form a long portfolio of stocks sold previously by a mutual fund. I start including stocks into the portfolio 3 months after the respective mutual fund sale in order to take lags in information availability into account. Each stock is then held for a predetermined holding period before it is eliminated from the portfolio. I report results for 3, 6 and 12-month holding periods. Weights

[10]Fama-French construct the short-term reversal factor *"from six value-weight portfolios formed using independent sorts on size and prior return of NYSE, AMEX, and NASDAQ stocks. ST_Rev is the average of the returns on two (big and small) low prior return portfolios minus the average of the returns on two high prior return portfolios. The portfolios are constructed monthly. Big means a firm is above the median market cap on the NYSE at the end of the previous month; small firms are below the median NYSE market cap. Prior return is measured from month - 1 to - 1. Firms in the low prior return portfolio are below the 30th NYSE percentile. Those in the high portfolio are above the 70th NYSE percentile."*.

are rebalanced on a monthly basis. Finally, I estimate alphas and beta risk coefficients of calendar time returns for equally and value weighed portfolios.

I find statistically significant positive alphas for 3-month holding periods for the equally weighted liquidity-trade sample, while there is no significant alpha for when using value-weighted portfolios. As equally weighted portfolios put a relatively larger weight on small-cap stocks, this seems to be a reasonable result, as liquidity provision is more important for less liquid assets. It is notable that for holding periods larger than 3 months, liquidity provision does not yield significant abnormal returns. The fact that a stand-alone liquidity provision strategy only provides limited abnormal returns can be seen as evidence that such a strategy has already been implemented by enough investors to almost eliminate abnormal returns.

I find that similar results hold for a strategy of trading stocks that have been voluntarily sold by mutual funds. For short holding periods, an equally weighted portfolio yields alphas that are significantly negative, while I cannot report statistical significance for longer holding periods. Results for both strategies are reported in Tables A.18 and A.19 in the Appendix.

Combining the two strategies I form zero-cost portfolios, long in liquidity driven sales and short in value driven sales with 3-month holding periods. I only include months for which it is possible to form a zero-cost portfolio, which requires at least one long and one short position. I find significant positive alphas for this strategy for both equally-weighted and value-weighted portfolios. The results are reported in Table A.20. This result shows the economic value of being able to infer the underlying reason for large trades by mutual funds.

As a robustness test, I estimate alphas after splitting the sample into two consecutive subsamples. While I do not find significant alphas in either sub-sample for the stand-alone strategies, I still find significant positive alphas of a similar order for the zero-cost portfolios.

3.6 Conclusion

While previous studies have documented the presence of front-running as an actively traded strategy before mutual fund fire-sales, there has been no clear evidence of liquidity provision after such a sale event. While front-running only requires the ability to predict mutual fund outflows and knowledge about fund holdings, in order to implement a profitable liquidity provision strategy an outside investor needs to be able to infer the underlying reason for each mutual fund sale.

I provide a methodological framework to disentangle liquidity-driven from value-motivated sales by mutual fund managers. Applying my framework and analyzing data on mutual fund transactions I find evidence for the presence of return reversal after liquidity-driven sales, while stocks subject to value-driven sales keep underperforming in the short run after the respective mutual fund-sale. I find a significantly faster speed for the return reversals compared to previous literature, when applying my framework as a sample selection method.

Additionally, I show that asset-liquidity itself is affected differently, depending on the sale motive, with assets sold for liquidity reasons returning to their pre-sale level of liquidity directly after the transaction, while assets sold for valuation exhibit lower levels of liquidity after such a sale.

Finally, I find that while liquidity provision as a stand-alone strategy only yields limited abnormal returns, it is possible to construct zero-cost portfolios with significantly positive alpha using the information contained in large mutual fund sales when taking contemporaneous flows into account.

In general, mutual funds are not able to avoid losses ex-ante from predatory trading strategies since their liquidity needs are easily predictable by any market participant. Nevertheless, while front-running imposes an extra cost for a fund, a timely liquidity provision strategy played by outsiders actually benefits a mutual fund, since competition between outside investors eager to provide liquidity reduces price pressure around a fire-sale.

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A Appendix

Table A.1: **PFC Summary Statistics (1996-2007)**
The table reports year-end summary statistics for the PFC measure from January 1994 to December 2007. The PFC coefficient is calculated as the correlation between fund's flows and the aggregated value weighted flows of all funds holding assets in the fund's current portfolio. Correlation is estimated in rolling 48 month windows, for monthly flows between 1992-2007. Column 2 reports the total number of flow correlation estimates. Columns 3+4 report the median and mean PFC coefficient, while Columns 5+6 report the minimum and maximum correlation. Column 7 reports the skewness.

Year	Number of Obs	Median PFC	Mean PFC	Min PFC	Max PFC	Skewness
1996	4038	0.26	0.30	-0.65	0.99	0.15
1997	5494	0.30	0.30	-0.52	1.00	0.01
1998	7231	0.29	0.30	-0.56	1.00	0.06
1999	8560	0.25	0.27	-0.67	1.00	0.19
2000	10189	0.27	0.29	-0.68	1.00	0.08
2001	10655	0.26	0.28	-0.63	1.00	0.13
2002	11227	0.27	0.28	-0.72	1.00	-0.03
2003	14007	0.26	0.28	-0.68	1.00	0.01
2004	16560	0.28	0.29	-0.70	1.00	0.11
2005	18808	0.28	0.29	-0.61	1.00	0.17
2006	20669	0.24	0.26	-0.58	1.00	0.18
2007	19836	0.21	0.23	-0.59	1.00	0.27

Table A.2: **Sample Summary Statistics (1992-2007)**

The table reports year-end summary statistics from January 1992 to December 2007 for the mutual fund sample selected from CDA/Spectrum Thompson Financial and CRSP Mutual Fund Database.It contains funds that, are not index or tax-managed funds, have total net assets exceeding five million dollars, and have an equity ratio of at least 0.75. Column 2 reports the total number of funds included in the sample. Column 3 reports the total net assets held ($M). Columns 4+5 report the median and average fund size while. Column 6 reports the percentage of market capitalization held by these funds. Column 7 reports the average number of stocks held by each fund. Columns 8+9 report the median and average annual return.

Year	Number of Funds	Total Net Assets ($M)	Median Fund Size ($M)	Mean Fund Size ($M)	Market-Cap	Mean Number of Assets	Median Annual Return	Mean Annual Return
1992	839	345247	104.6	411.5	7.9%	121	7.34%	7.40%
1993	1118	532022	111.8	475.9	10.7%	136	10.01%	11.78%
1994	1215	620361	115.6	510.6	11.6%	141	-1.22%	-1.53%
1995	1454	832040	118.3	572.2	13.2%	147	25.99%	24.00%
1996	1714	1187273	125.1	692.7	15.0%	147	16.83%	15.67%
1997	1897	1630931	142.1	859.7	15.8%	154	21.94%	18.45%
1998	2135	2093324	143.3	980.5	17.0%	155	14.09%	13.04%
1999	2322	2637779	150.4	1136.0	17.8%	155	21.10%	26.64%
2000	2534	3305581	176.8	1304.5	20.1%	168	-0.88%	-0.48%
2001	2726	2768999	146.8	1015.8	21.9%	163	-8.99%	-8.16%
2002	2853	2387925	123.9	837.0	24.3%	165	-20.96%	-20.49%
2003	2966	2417926	121.9	815.2	19.2%	168	28.44%	29.34%
2004	2928	3089303	162.0	1055.1	22.3%	177	12.33%	12.72%
2005	2971	3540238	182.7	1191.6	24.3%	175	7.62%	8.70%
2006	2848	4138811	237.4	1453.2	26.7%	179	13.62%	13.85%
2007	2869	4692274	262.1	1635.5	31.4%	176	6.67%	7.36%

Table A.3: **Fund Portfolio Characteristics (1994-2007)**
The table reports the characteristics of portfolios held by mutual funds for the period between January 1996 to December 2007, as well as in 4-year subsamples. PFC is estimated in rolling 48 month windows, using monthly flows from 1992-2007. The same windows are used to estimate the 3-factor Fama-French and 4-factor Carhart alphas and betas. Liquidity is shown as the average of the portfolio-level Amihud ratio. Average portfolio concentration is reported by means of the adjusted Herfindahl index. Also shown are the average number of stocks held in each fund portfolio and the average fund's age in months.

	Mean 1996-1999	Mean 2000-2003	Mean 2004-2007	Mean 1996-2007
PFC	0.29	0.28	0.26	0.27
monthly alpha (3 factor)	-0.15%	-0.11%	-0.06%	-0.09%
monthly alpha (4 factor)	-0.18%	-0.11%	-0.09%	-0.11%
Beta Mkt	0.95	1.01	1.00	0.99
Beta SmB	0.21	0.16	0.21	0.19
Beta HmL	0.01	0.12	0.04	0.06
Beta MoM	0.03	0.00	0.03	0.02
Amihud Ratio	0.16	0.11	0.06	0.09
Adj. Herfindahl Index	0.010	0.009	0.011	0.010
Number of Stocks held	120	123	136	130
Fund Age (months)	74	97	117	103

Table A.4: **PFC Measure Determinants (1996-2007)**

The table reports the relationship between portfolio-adjusted flow correlation (PFC) and other portfolio characteristics. It shows the results of regressing portfolio risk factor loadings, portfolio concentration, liquidity, age of the fund and lagged excess return on PFC. Risk factor loadings are the beta coefficients of fund returns from the 3 Fama-French and momentum factor model estimated in backward looking 48-month rolling windows. Dummies Ds, Dh and Dm indicate high factor load. Portfolio liquidity is the logarithm of the value weighted average of the asset Amihud ratio. Concentration is measured by the log of the adjusted Herfindahl index. Fund age in months is included to account for fund growth effects such as size, reputation, imitation by peer funds, etc. To compensate for fixed time effects the sample month is included in the regression. Lagged excess returns are the cumulative 12-month 4-factor alpha of the fund. The coefficients reported in this table are estimated with pooled OLS regressions with White standard errors. T-statistics are shown in parentheses. Estimates significant at the 5% level are printed in bold.

	Dependent Variable = PFC						
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Intercept	**0.296**	**0.286**	**0.280**	**0.280**	**0.279**	**0.236**	**0.249**
	(74.88)	(71.81)	(74.22)	(71.34)	(68.57)	(57.84)	(55.26)
MKT	**0.016**	**0.027**	**0.024**	**0.022**	**0.016**	**0.035**	**-0.012**
	(4.44)	(7.48)	(6.82)	(6.26)	(4.54)	(9.89)	(-3.25)
SMB	**0.151**	**0.150**	**0.115**	**0.192**	**0.154**	**0.162**	**0.15**
	(75.28)	(74.20)	(53.40)	(93.79)	(75.68)	(67.00)	(37.10)
Ds*SMB							**0.01**
							(2.18)
HML	0.002	**0.006**	**-0.012**	**0.013**	**0.004**	0.003	**-0.09**
	(0.84)	(3.13)	(-6.27)	(7.21)	(2.08)	(1.46)	(-34.88)
Dh*HML							**0.15**
							(39.49)
MOM	**0.016**	**0.021**	0.007	**0.028**	**0.017**	**0.021**	**-0.04**
	(4.00)	(5.00)	(1.64)	(6.82)	(4.06)	(5.04)	(-5.45)
Dm*MOM							**0.06**
							(6.50)
Lag(Alpha)		**0.176**				**0.079**	**0.051**
		(19.24)				(8.79)	(5.40)
Log(Amihud)			**0.040**			**0.210**	**0.018**
			(47.19)			(24.67)	(19.09)
Log(Herfindahl)				**0.060**		**0.053**	**0.045**
				(82.86)		(70.80)	(56.31)
Fund Age(mth)					**0.0003**	**0.0004**	**0.0005**
					(17.08)	(20.14)	(24.50)
Month Index	**-0.0006**	**-0.0006**	**-0.0004**	**-0.0006**	**-0.0008**	**-0.0006**	**-0.0005**
	(-37.81)	(-38.07)	(-24.47)	(-36.33)	(-41.55)	(-32.34)	(-22.15)
N Obs	141,510	141,510	141,510	141,510	141,510	141,510	141,510
Adj R^2	4.40%	4.62%	4.78%	8.31%	4.58%	8.89%	9.41%

Table A.5: **PFC Decile Portfolios (1996-2007)**

The table illustrates decile portfolio returns of portfolios of mutual funds sorted by flow correlation. D1 is the portfolio of funds with the lowest flow correlation coefficient, D5 is the median portfolio and D10 are the funds with the highest level of flow correlation. The left panel shows the results when re-sorting the cross-section of funds into deciles each month, while in the right panel all fund-month observations have been pooled before constructing decile portfolios. Returns are cumulative in excess of the risk free rate, the 3 Fama-French factors and 4 factors including momentum. T-statistics are shown in parentheses. Estimates significant at the 5% level are printed in bold.

		monthly deciles				pooled deciles			
cumulative		1m	3m	6m	12m	1m	3m	6m	12m
excess r_f	D1	0.04%	**-0.23%**	**0.55%**	**2.29%**	**0.38%**	**0.84%**	**1.85%**	**1.21%**
		(1.02)	(-2.58)	(4.25)	(10.5)	(9.02)	(9.68)	(14.76)	(5.26)
	D5	**0.18%**	-0.07%	**0.75%**	**3.02%**	**0.55%**	**1.24%**	**2.57%**	**2.67%**
		(4.12)	(-0.82)	(5.72)	(13.42)	(12.42)	(14.54)	(21.48)	(12.13)
	D10	0.01%	**-0.32%**	**0.48%**	**2.28%**	**0.33%**	**0.97%**	**2.10%**	**3.02%**
		(0.23)	(-3.03)	(3.18)	(9.12)	(5.69)	(8.63)	(13.07)	(11.33)
excess 3 factor	D1	**-0.13%**	**-0.39%**	**-0.75%**	**-1.30%**	**-0.14%**	**-0.38%**	**-0.74%**	**-1.20%**
		(-7.54)	(-12.15)	(-15.22)	(-15.25)	(-7.5)	(-11.05)	(-13.89)	(-13.88)
	D5	**-0.08%**	**-0.31%**	**-0.62%**	**-1.14%**	**-0.09%**	**-0.30%**	**-0.63%**	**-1.10%**
		(-4.19)	(-9.03)	(-11.91)	(-12.04)	(-4.54)	(-8.09)	(-10.94)	(-11.89)
	D10	**-0.15%**	**-0.38%**	**-0.70%**	**-1.21%**	**-0.15%**	**-0.41%**	**-0.81%**	**-1.81%**
		(-6.58)	(-8.73)	(-10.67)	(-10.99)	(-5.46)	(-8.19)	(-10.83)	(-15.58)
excess 4 factor	D1	**-0.15%**	**-0.45%**	**-0.88%**	**-1.64%**	**-0.15%**	**-0.44%**	**-0.90%**	**-1.64%**
		(-9.14)	(-14.86)	(-18.24)	(-19.85)	(-8.64)	(-13.14)	(-17.44)	(-19.75)
	D5	**-0.11%**	**-0.41%**	**-0.80%**	**-1.40%**	**-0.11%**	**-0.35%**	**-0.72%**	**-1.35%**
		(-6.29)	(-12.62)	(-15.73)	(-15.49)	(-5.27)	(-9.85)	(-13.01)	(-15.31)
	D10	**-0.18%**	**-0.48%**	**-0.86%**	**-1.51%**	**-0.16%**	**-0.45%**	**-0.87%**	**-1.89%**
		(-7.85)	(-11.22)	(-13.07)	(-13.91)	(-6.20)	(-9.19)	(-11.79)	(-16.59)

Table A.6: **125-Style Matched Portfolios (3-factor Quintiles) (1996-2007)**

The table reports cumulative 4-factor excess returns of decile portfolios matched by factor style. The first panel reports average returns for the entire sample of funds, the second panel for the sub-sample of funds that are not factor tracking funds . The last panel reports results for factor tracking funds only. First, for each panel the respective sample of funds was divided into quintiles for the size, value and momentum factor, resulting in 125 style-brackets. Within each style the pooled fund-month observations were sorted into deciles by their PFC. Cumulative returns are forward-looking, out of sample Carhart-alphas for 1, 3, 6 and 12 month horizons. T-statistics are shown in parentheses. Estimates significant at the 5% level are printed in bold.

	Style-Matched	cumulative 4-factor excess return			
	Correlation Decile	1m	3m	6m	12m
Full sample	D1	**-0.11%**	**-0.28%**	**-0.65%**	**-1.03%**
		(-3.55)	(-3.58)	(-5.00)	(-4.41)
	D5	**-0.10%**	**-0.34%**	**-0.68%**	**-1.50%**
		(-2.64)	(-4.15)	(-4.75)	(-6.47)
	D10	**-0.14%**	**-0.38%**	**-0.71%**	**-1.75%**
		(-3.01)	(-2.88)	(-2.66)	(-4.23)
	D1-10	0.03%	0.09%	0.06%	0.71%
		(-0.16)	(-0.47)	(-0.93)	(0.50)
non factor	D1	**-0.11%**	**-0.29%**	**-0.67%**	**-1.02%**
		(-2.18)	(-2.22)	(-3.37)	(-2.43)
	D5	**-0.12%**	**-0.42%**	**-0.82%**	**-1.63%**
		(-2.89)	(-4.51)	(-5.72)	(-7.22)
	D10	**-0.20%**	**-0.60%**	**-1.15%**	**-2.45%**
		(-4.62)	(-6.01)	(-5.93)	(-6.74)
	D1-10	0.10%	**0.31%**	**0.48%**	**1.43%**
		(1.63)	(1.97)	(2.11)	(2.71)
factor only	D1	**-0.11%**	**-0.26%**	**-0.56%**	**-1.08%**
		(-2.18)	(-1.93)	(-2.75)	(-2.82)
	D5	0.01%	-0.03%	-0.12%	-0.98%
		(0.06)	(-0.12)	(-0.26)	(-1.15)
	D10	0.12%	**0.52%**	**1.03%**	**1.07%**
		(1.19)	(2.3)	(2.07)	(1.15)
	D1-10	**-0.23%**	**-0.78%**	**-1.60%**	**-2.15%**
		(-1.99)	(-3.25)	(-3.03)	(-2.20)

Table A.7: **PFC and style matched performance (1996-2007)**

The table reports the average coefficients from regressing PFC on 12 month cumulative 4-factor excess returns of decile portfolios matched by factor style. First the sample of fund returns was divided into quintiles for the size, value and momentum factor, resulting in 125 style-brackets. This table reports results from the sub-sample of non-factor tracking funds. Within each style the coefficients from regression $cumExRet_{i,(t+12)} = \alpha + \beta_1\rho_{i,t} + \beta_2 Lag(ExRet)_{i,(t-1)} + \beta_3 Log(Ami_{i,t}) + \beta_4 Log(Herf_{i,t}) + \beta_5 Age_{i,t} + \beta_6 Log(FundSize_{i,t}) + \beta_7 SampleMonth_t + \epsilon_{i,t}$ were determined and averaged across styles. Control variables are lagged 4-factor portfolio excess return, log of portfolio liquidity measured by the Amihud ratio, log of portfolio concentration measured by the adj. Herfindahl index, fund age, log of fund size and a sample time index. T-statistics are shown in parentheses. Estimates significant at the 5% level are printed in bold.

Dep. Var. = cumulative 12-month 4-factor ex return	
Intercept	-0.10%
	(-0.25)
Flow Correlation	**-1.44%**
	(-3.64)
Lag(Alpha)	-1.05%
	(-0.29)
Log(Amihud)	0.37%
	(1.83)
Log(Herfindahl)	**0.77%**
	(7.45)
Fund Age	0.00%
	(1.20)
Log(Fund Size)	-0.12%
	(1.55)
Month Index	**-0.00%**
	(-2.43)
N Obs	95,987
Adj R^2	7.53%

Table A.8: **Upper Bound Exceedance (1996-2007)**

The table reports statistics on exceedance of funds' upper bounds per year and for the whole sample. The first column of results shows the median fund's upper bound, the second column shows the median difference between flow correlation and the upper bound, so the median bound exceedance. The third column shows the percentage of funds that on average exceeded the bound during the calendar year.

Year	Upper bound Median	Corr - bound Median	Proportion of funds exceeding upper bound
1996	0.34	-0.15	39.67%
1997	0.43	-0.25	38.96%
1998	0.54	-0.30	35.94%
1999	0.74	-0.55	30.45%
2000	1.02	-0.86	25.42%
2001	0.97	-0.75	26.01%
2002	1.05	-0.82	26.28%
2003	1.27	-1.08	25.34%
2004	1.63	-1.36	22.02%
2005	1.53	-1.35	21.56%
2006	1.30	-1.12	23.01%
2007	1.06	-0.94	23.82%
Sample	0.99	-0.79	28.21%

Table A.9: **Reduction in Bid-Ask Spread**

The table reports average bid-ask spreads as percentage of average portfolio price before tick reduction, change in the average bid-ask spread as percentage of price after the reduction, average Amihud illiquidity measure.The sample contains 400 daily observations. All quoted spread reductions are significantly different from zero at 95% confidence.

NYSE	Liquid P1	P2	P3	P4	Illiquid P5
	Reduction of Tick size from 1/16$ to 1/100$				
Pre-event Bid-Ask	**0.99%**	**1.29%**	**1.69%**	**2.06%**	**2.74%**
Post minus Pre	**-0.37%**	**-0.68%**	**-0.96%**	**-1.25%**	**-1.66%**
Amihud *ILLIQ*	0.05	0.27	0.90	2.51	14.06

Table A.10: **Trading Volume**

Average daily trading volume in 1M$ before and after Tick reduction from 1/16$ to 1/100$, as well as volatility of daily trading volume for NYSE liquidity portfolios. 400 daily Observations. P-values are quoted for significance in difference in mean volume and variance.

NYSE	Liquid P1	P2	P3	P4	Illiquid P5
	Average daily trading volume				
Pre-event Volume	**110,959**	**11,123**	**3,166**	**1,216**	**566**
Post minus Pre	**-7,586**	**1,666**	**422**	**127**	**29**
Percentage Change	**-6.8%**	**15.0%**	**13.4%**	**10.4%**	**5.1%**
p-value	0.00	0.00	0.00	0.00	0.02
	Volatility of trading volume				
Pre-event Volatility of Volume	**21,121**	**2,155**	**579**	**237**	**127**
Post minus Pre	-693	-102	-10	13	**20**
Percentage Change	-3.2 %	-4.7 %	-1.7%	5.4%	**15.8%**
p-value	0.32	0.25	0.41	0.23	0.02

Table A.11: **Difference in difference estimation**

3-day Scholes-Williams estimator regressions of 3-factor Fama-French model. Dependent variables are daily portfolio excess returns of equally weighted zero-cost portfolios long in liquid and short in illiquid assets. 2 sets of dummys and interaction dummy for difference in difference estimation before and after the tick reduction event and between NYSE treatment and NASDAQ/AMEX (Na/Am) control group. 400 daily observations for each group. The intercept is omitted from the table. Standard errors have been bootstrapped and are quoted in parenthesis.

Liquid - illiquid	*Pre Event*		*Post minus Pre*	
zero cost portfolios	NYSE	Δ Na/Am	NYSE	Δ Na/Am
		Market Factor		
β_{Market}	**0.48**	**0.35**	**-0.41**	**0.46**
Std. Err	(0.10)	(0.11)	(0.13)	(0.20)
		Size Factor		
β_{SMB}	**-0.56**	**0.68**	-0.13	**0.49**
Std. Err	(0.17)	(0.24)	(0.22)	(0.19)
		Value Factor		
β_{HML}	0.26	**-0.66**	**-0.55**	0.29
Std. Err	(0.20)	(0.24)	(0.17)	(0.27)

Table A.12: **NYSE Liquidity Portfolios**

3-day Scholes-Williams estimator regressions. 3 Fama-French factors. Dependent variables are daily portfolio excess returns of equally weighted and liquidity sorted portfolios of NYSE assets. 400 daily observations. The intercepts are omitted from the table. Standard errors are bootstrapped and are quoted in parenthesis.

NYSE	Liquid P1	P2	P3	P4	Illiquid P5
			Market Factor		
Pre-event	**0.96**	**0.87**	**0.70**	**0.55**	**0.48**
Std. Err	(0.07)	(0.07)	(0.06)	(0.05)	(0.07)
Post minus Pre	0.06	0.13	0.13	**0.23**	**0.47**
Std. Err	(0.07)	(0.08)	(0.07)	(0.07)	(0.09)
			Size Factor		
Pre-event	-0.11	0.13	**0.34**	**0.39**	**0.45**
Std. Err	(0.09)	(0.12)	(0.09)	(0.08)	(0.10)
Post minus Pre	**0.25**	**0.26**	**0.23**	**0.27**	**0.38**
Std. Err	(0.11)	(0.13)	(0.11)	(0.12)	(0.14)
			Value Factor		
Pre-event	**0.42**	**0.47**	**0.43**	**0.33**	**0.16**
Std. Err	(0.07)	(0.10)	(0.08)	(0.07)	(0.09)
Post minus Pre	-0.11	0.02	0.01	0.17	**0.44**
Std. Err	(0.10)	(0.11)	(0.09)	(0.09)	(0.11)
R^2	92%	87%	88%	87%	81%

Table A.13: **NASDAQ/AMEX Liquidity Portfolios**
3-day Scholes-Williams estimator regressions. 3 Fama-French factors. Dependent variables are daily portfolio excess returns of equally weighted and liquidity sorted portfolios of NASDAQ/AMEX assets. 400 daily observations. The intercepts are omitted from the table. Standard errors are bootstrapped and are quoted in parenthesis.

Na/Am	Liquid P1	P2	P3	P4	Illiquid P5
			Market Factor		
Pre-event	**1.30**	**0.94**	**0.67**	**0.50**	**0.47**
Std. Err	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Post minus Pre	0.05	0.07	-0.04	-0.02	0.00
Std. Err	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)
			Size Factor		
Pre-event	**0.86**	**1.05**	**0.88**	**0.67**	**0.74**
Std. Err	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)
Post minus Pre	0.03	-0.08	**-0.38**	**-0.33**	**-0.33**
Std. Err	(0.09)	(0.09)	(0.10)	(0.10)	(0.12)
			Value Factor		
Pre-event	**-0.17**	**0.17**	**0.30**	**0.26**	**0.23**
Std. Err	(0.07)	(0.07)	(0.08)	(0.08)	(0.10)
Post minus Pre	**-0.31**	-0.02	**-0.16**	-0.12	-0.05
Std. Err	(0.10)	(0.10)	(0.10)	(0.10)	(0.13)
R^2	95%	90%	75%	61%	48%

Table A.14: **Monthly cumulative average abnormal returns and asset-liquidity of stocks around funding-liquidity driven mutual fund sales**

Cumulative average abnormal returns (CAAR) are measured in excess of a single factor market model for the 12 month prior and 18 months after a sale event. The column reporting results conditional on portfolio weights and size of the sale are the sale events within the bottom percentile of $PRESSURE_{i,t}^{forced} = \frac{\sum_j (\Delta Holdings_{i,j,t} | \omega_{i,j,t-1} \leq \omega_{i,j,t} < \omega^*_{i,j})}{AvgVol_{i,t-12,t-6}}$ which is the relative change in holdings conditional on the post-adjustment portfolio weight being in the interval $(\omega^*_t, \omega_{(t-1)}]$, with $\omega^*_t = (1 - \frac{Flow_t}{TNA_t})\omega_{(t-1)}$. Additionally the last column provides the amihud-ratio for this specification, normalized with respect to the first month of the event window. Relative ratios that are significantly different from 1 at 95% confidence are marked with a *. The column reporting CAAR results conditional on distress and size are bottom percentile of the sale events as specified according to Coval and Stafford (2007) as $PRESSURE\_1_{i,t} = \frac{\sum_j (\Delta Holdings_{j,i,t}) | flow\%_{j,t} < P(10th))}{AvgVolume_{i,t-12,t-6}}$ which is the relative transaction volume conditional on the fund being in the top decile of distress. The test statistics are calculated using the standard error of the mean. The number of event windows used in each sample is provided at the bottom of the table.

Table A.14: **Monthly cumulative average abnormal returns and asset-liquidity of stocks around funding-liquidity driven mutual fund sales**

	Conditional on Portfolio weights &Size		Conditional on Distress & Size		
Eventmonth	CAAR	t-statistic	CAAR	t-statistic	Normalized Amihud
-12	-2.0%	(-2.54)	-2.6%	(-3.46)	n/a
-11	-2.8%	(-3.89)	-2.8%	(-2.70)	1.31 *
-10	-4.3%	(-4.22)	-5.1%	(-3.98)	1.77 *
-9	-5.0%	(-4.43)	-7.5%	(-4.16)	1.50 *
-8	-7.6%	(-4.29)	-8.6%	(-5.92)	2.26
-7	-9.4%	(-4.53)	-10.3%	(-6.98)	1.73 *
-6	-10.7%	(-6.20)	-12.5%	(-6.86)	1.42 *
-5	-12.1%	(-6.34)	-13.0%	(-7.39)	1.19 *
-4	-13.3%	(-7.31)	-14.8%	(-6.81)	1.38 *
-3	-15.2%	(-6.99)	-16.3%	(-6.65)	1.15
-2	-17.6%	(-8.46)	-19.0%	(-7.49)	1.15
-1	-18.6%	(-8.75)	-20.4%	(-7.49)	1.30
0	-20.8%	(-8.85)	-22.2%	(-7.66)	1.06
1	-16.2%	(-6.79)	-20.4%	(-5.17)	1.01
2	-12.7%	(-5.77)	-18.0%	(-4.36)	1.16
3	-9.7%	(-5.24)	-17.9%	(-4.48)	1.00
4	-9.0%	(-4.39)	-17.4%	(-4.98)	1.07
5	-8.1%	(-4.52)	-17.3%	(-4.60)	1.08
6	-8.0%	(-3.87)	-16.8%	(-3.44)	0.85 *
7	-8.3%	(-2.27)	-14.8%	(-3.58)	1.00
8	-7.2%	(-1.92)	-13.4%	(-3.00)	1.21
9	-7.4%	(-1.43)	-13.0%	(-3.11)	0.88
10	-9.2%	(-1.38)	-14.3%	(-3.64)	1.10
11	-8.3%	(-2.18)	-15.8%	(-3.17)	1.84
12	-8.1%	(-1.90)	-15.5%	(-3.06)	1.05
13	-8.6%	(-2.07)	-16.4%	(-3.19)	1.12
14	-7.2%	(-1.67)	-16.4%	(-3.77)	1.17
15	-7.7%	(-1.45)	-16.0%	(-2.86)	0.93
16	-7.6%	(-1.00)	-15.1%	(-2.60)	0.85
17	-6.8%	(-0.65)	-14.7%	(-2.02)	1.10
18	-7.1%	(-0.88)	-13.8%	(-2.19)	0.85
N (Events)	282		415		

Table A.15: **Monthly cumulative average abnormal returns and asset-liquidity of stocks around mutual fund sales in excess of funding-liquidity needs**

Cumulative average abnormal returns (CAAR) are measured in excess of a single factor market model for the 12 month prior and 18 months after a sale event. The table reports results for the sale events within the bottom percentile of $PRESSURE_{i,t}^{overscaling} = \frac{\sum_j (\Delta Holdings_{i,j,t} | \omega_{i,j,t} < \omega_{i,j,t-1} AND flow\%_{j,t} < P(10))}{AvgVol_{i,t-12,t-6}}$ which is the relative change in holdings conditional on the post-adjustment portfolio weight being reduced, so for disproportionately large sales with respect to funding outflows for funds in distress. Additionally the last column provides the amihud-ratio, normalized with respect to the first month of the event window. Relative ratios that are significantly different from 1 at 95% confidence are marked with a *. The test statistics are calculated using the standard error of the mean. The number of event windows used is provided at the bottom of the table.

Table A.15: **Monthly cumulative average abnormal returns and asset-liquidity of stocks around mutual fund sales in excess of funding-liquidity needs**

Eventmonth	CAAR	t-statistic	Normalized Amihud
-12	-1.0%	(-1.90)	n/a
-11	-1.7%	(-2.02)	1.27 *
-10	-3.1%	(-3.17)	1.60 *
-9	-4.3%	(-3.94)	1.46 *
-8	-6.5%	(-5.88)	1.48 *
-7	-8.1%	(-6.81)	1.75 *
-6	-8.8%	(-6.70)	1.61 *
-5	-9.7%	(-6.98)	1.54 *
-4	-12.6%	(-6.57)	1.74 *
-3	-13.8%	(-6.42)	1.68 *
-2	-15.7%	(-6.86)	1.94 *
-1	-17.8%	(-6.79)	2.38
0	-19.2%	(-6.78)	1.30 *
1	-15.2%	(-5.82)	1.18 *
2	-15.7%	(-5.16)	1.26
3	-15.1%	(-6.17)	0.84 *
4	-15.7%	(-6.82)	0.95
5	-15.3%	(-6.37)	1.07
6	-14.8%	(-6.11)	0.99
7	-16.4%	(-5.66)	1.11
8	-15.4%	(-5.23)	1.25
9	-16.1%	(-5.43)	0.98
10	-17.5%	(-5.85)	1.07
11	-18.3%	(-6.07)	1.44
12	-18.0%	(-5.87)	1.08
13	-18.1%	(-5.81)	0.97
14	-19.9%	(-6.33)	1.26
15	-20.2%	(-6.38)	1.22
16	-19.4%	(-6.10)	1.12
17	-20.8%	(-5.56)	1.13
18	-21.0%	(-5.58)	1.26
N (Events)	315		

Table A.16: **Monthly cumulative average abnormal returns and asset-liquidity of stocks around mutual fund sales not driven by funding-liquidity needs**

Cumulative average abnormal returns (CAAR) are measured in excess of a single factor market model for the 12 month prior and 18 months after a sale event. The table reports results for the sale events within the bottom percentile of $PRESSURE_{i,t}^{unforced} = \frac{\sum_j (\Delta Holdings_{i,j,t} | \omega_{i,j,t} < \omega_{i,j,t-1} AND flow\%_{j,t} > P(10))}{AvgVol_{i,t-12,t-6}}$ which is the relative change in holdings conditional on the post-adjustment portfolio weight being reduced, conditional of funding outflows not being in the bottom decile, so for funds which are not in distress. Additionally the last column provides the amihud-ratio, normalized with respect to the first month of the event window. Relative ratios that are significantly different from 1 at 95% confidence are marked with a *. The test statistics are calculated using the standard error of the mean. The number of event windows used is provided at the bottom of the table.

Table A.16: **Monthly cumulative average abnormal returns and asset-liquidity of stocks around mutual fund sales not driven by funding-liquidity needs**

Eventmonth	CAAR	t-statistic	Normalized Amihud
-12	-0.6%	(-1.54)	n/a
-11	-1.7%	(-1.89)	1.20 *
-10	-3.2%	(-2.22)	1.18 *
-9	-4.6%	(-2.43)	1.24 *
-8	-5.1%	(-2.29)	1.24 *
-7	-6.8%	(-3.53)	1.37 *
-6	-7.1%	(-4.20)	1.41 *
-5	-7.8%	(-4.34)	1.26 *
-4	-9.0%	(-4.31)	1.21 *
-3	-10.0%	(-4.99)	1.30 *
-2	-10.6%	(-4.46)	1.24 *
-1	-11.1%	(-4.75)	1.40 *
0	-9.7%	(-4.85)	1.22 *
1	-9.2%	(-4.79)	1.31 *
2	-8.1%	(-4.77)	1.45 *
3	-9.2%	(-4.24)	1.22 *
4	-10.3%	(-4.39)	1.49 *
5	-10.2%	(-4.52)	1.69 *
6	-12.1%	(-3.87)	1.29
7	-12.7%	(-4.27)	1.44 *
8	-14.0%	(-4.92)	1.57 *
9	-15.5%	(-4.43)	1.68 *
10	-15.4%	(-4.38)	1.46 *
11	-16.4%	(-4.18)	1.39
12	-17.3%	(-4.90)	1.28
13	-18.3%	(-5.07)	1.40 *
14	-18.9%	(-4.67)	1.39 *
15	-19.7%	(-4.45)	1.33
16	-21.2%	(-5.00)	1.60 *
17	-22.0%	(-4.65)	1.49 *
18	-23.2%	(-4.88)	1.60 *
N (Events)	758		

Table A.17: **Short-term Reversal**

The dependent variable in these regressions are monthly event-window stock returns in excess of the risk-free rate. Additionally to the Fama-French short-term-reversal factor I include standard set of Fama-French risk factors, namely the return on the value-weighted market portfolio in excess of the riskfree rate, the size and value factor, and momentum. I first estimate regression coefficients separately for each event window and then estimate the mean of each regression coefficient. N denotes the number of event window regressions, t-statistics are calculated from the standard errors of the mean estimate and are provided in parentheses.

Liquidity driven fire-sales					
Intercept	Rm-Rf	SMB	HML	UMD	Reversal
0.00%	0.74	0.53	0.66	-0.01	0.10
(0.69)	(19.98)	(14.64)	(13.44)	(-0.18)	(2.83)
N =	282				
Overscaling					
Intercept	Rm-Rf	SMB	HML	UMD	Reversal
0.00%	0.92	0.49	0.58	-0.09	0.06
(1.62)	(20.05)	(10.14)	(11.11)	(-3.90)	(1.08)
N =	123				
Unforced Sales					
Intercept	Rm-Rf	SMB	HML	UMD	Reversal
-0.01%	0.96	0.42	0.32	-0.06	-0.02
(-7.65)	(32.87)	(13.75)	(8.53)	(-2.50)	(-0.75)
N =	758				

Table A.18: **Liquidty Provision as Trading Strategy (1990-2008)**

The dependent variable in these regressions are monthly calendar time portfolio returns in excess of the risk-free rate. I construct portfolios of stocks that fall into the top percentile of fire sales (in terms of transaction volume relative to the average trading volume of the stock) by mutual funds for which the sale does not lead to a reduction in the stocks' relative weights within the respective fund's holdings. Portfolios are constructed monthly using equal and value weights. Stocks are included starting 3 months after the respective fire sale event and are held for 3, 6 or 12 months after inclusion. I control for the three Fama-French risk factors, namely the return on the value-weighted market portfolio in excess of the riskfree rate, the size and value factor, and momentum. N denotes the number of monthly return observations, t-statistics are provided in parentheses.

3-month holding period

Equally weighted						Value weighted					
Intercept	Rm-Rf	SMB	HML	UMD	R^2	Intercept	Rm-Rf	SMB	HML	UMD	R^2
0.66%	0.69				0.20	0.39%	0.81				0.21
(2.24)	(5.44)					(0.65)	(5.68)				
0.68%	0.70	0.23	0.11		0.21	-0.40%	0.82	0.07	0.04		0.21
(2.24)	(4.61)	(1.47)	(0.54)			(-0.64)	(4.78)	(0.41)	(0.19)		
0.36%	0.58	0.33	0.08	-0.28	0.25	-0.44%	0.84	0.06	0.05	0.04	0.21
(1.66)	(3.73)	(2.10)	(0.40)	(-2.57)		(-0.069)	(4.63)	(0.32)	(0.21)	(0.28)	
N =	123					N =	123				

6-month holding period

Equally weighted						Value weighted					
Intercept	Rm-Rf	SMB	HML	UMD	R^2	Intercept	Rm-Rf	SMB	HML	UMD	R^2
-0.47%	0.67				0.21	0.00%	0.93				0.22
(-1.12)	(6.66)					(0.00)	(6.91)				
-0.57%	0.70	0.21	0.13		0.22	0.03%	0.91	0.01	-0.05		0.22
(-1.31)	(5.83)	(1.68)	(0.86)			(0.05)	(5.66)	(0.04)	(-0.24)		
-0.08%	0.56	0.29	0.06	-0.40	0.31	0.37%	0.81	0.06	-0.10	-0.27	0.25
(-0.18)	(4.85)	(2.45)	(0.40)	(-4.83)		(0.63)	(4.99)	(0.37)	(-0.48)	(-2.35)	
N =	171					N =	171				

12-month holding period

Equally weighted						Value weighted					
Intercept	Rm-Rf	SMB	HML	UMD	R^2	Intercept	Rm-Rf	SMB	HML	UMD	R^2
-0.11%	0.64				0.24	-0.19%	1.03				0.32
(-0.34)	(7.90)					(-0.28)	(9.66)				
-0.43%	0.77	0.31	0.42		0.30	-0.29%	1.16	-0.12	0.25		0.34
(-1.30)	(8.41)	(3.16)	(3.52)			(-0.65)	(9.46)	(-0.94)	(1.55)		
0.04%	0.65	0.38	0.34	-0.40	0.42	0.09%	1.06	-0.06	0.19	-0.32	0.38
(0.12)	(7.63)	(4.29)	(3.13)	(-6.35)		(0.19)	(8.74)	(-0.48)	(1.20)	(-3.54)	
N =	198					N =	198				

Table A.19: **Voluntary Mutual Fund Sales as Trading Strategy (1990-2008)**

The dependent variable in these regressions are monthly calendar time portfolio returns in excess of the risk-free rate. I construct portfolios of stocks that fall into the top percentile of voluntary sales (in terms of transaction volume relative to the average trading volume of the stock) by non-distressed mutual funds, so fund that do not experience outflows within the top decile of redemptions. Portfolios are constructed monthly using equal and value weights. Stocks are included starting 3 months after the respective sale event and are held for 3, 6 or 12 months after inclusion. I control for the three Fama-French risk factors, namely the return on the value-weighted market portfolio in excess of the riskfree rate, the size and value factor, and momentum. N denotes the number of monthly return observations, t-statistics are provided in parentheses.

3-month holding period

Equally weighted						Value weighted					
Intercept	Rm-Rf	SMB	HML	UMD	R^2	Intercept	Rm-Rf	SMB	HML	UMD	R^2
-1.23%	0.94				0.37	-0.38%	1.10				0.32
(-3.44)	(10.58)					(-0.80)	(9.46)				
-1.39%	0.95	0.37	0.19		0.41	-0.15%	0.89	0.44	-0.33		0.40
(-3.84)	(9.57)	(3.53)	(1.47)			(-0.32)	(6.95)	(3.25)	(-2.00)		
-1.09%	0.88	0.44	0.16	-0.27	0.45	-0.22%	0.90	0.42	-0.32	0.06	0.40
(-3.02)	(8.96)	(4.23)	(1.23)	(-3.68)		(-0.47)	(6.93)	(3.08)	(-1.95)	(0.66)	
N =	192					N =	192				

6-month holding period

Equally weighted						Value weighted					
Intercept	Rm-Rf	SMB	HML	UMD	R^2	Intercept	Rm-Rf	SMB	HML	UMD	R^2
-0.53%	1.02				0.54	0.24%	1.17				0.54
(-1.98)	(15.29)					(0.79)	(15.24)				
-0.75%	1.08	0.35	0.26		0.59	0.33%	1.09	0.16	-0.13		0.56
(-2.81)	(14.54)	(4.51)	(2.77)			(1.03)	(12.39)	(1.70)	(-1.15)		
-0.43%	0.99	0.41	0.22	-0.29	0.65	0.33%	1.09	0.16	-0.13	0.00	0.56
(-1.68)	(14.09)	(5.60)	(2.42)	(-5.59)		(1.01)	(12.06)	(1.68)	(-1.15)	(-0.05)	
N =	198					N =	198				

12-month holding period

Equally weighted						Value weighted					
Intercept	Rm-Rf	SMB	HML	UMD	R^2	Intercept	Rm-Rf	SMB	HML	UMD	R^2
-0.22%	0.99				0.64	0.43%	1.13				0.67
(-1.04)	(18.92)					(1.90)	(20.08)				
-0.44%	1.07	0.26	0.31		0.68	0.51%	1.07	0.01	-0.12		0.67
(-2.16)	(18.79)	(4.31)	(4.14)			(2.20)	(16.63)	(0.21)	(-1.46)		
-0.14%	1.00	0.32	0.26	-0.27	0.74	0.50%	1.08	0.01	-0.12	0.01	0.67
(-0.75)	(19.09)	(5.74)	(3.90)	(-7.02)		(2.08)	(16.31)	(0.17)	(-1.42)	(0.26)	
N =	204					N =	204				

Table A.20: **Zero Cost Portfolios (1990-2008)**

The dependent variable in these regressions are monthly calendar time portfolio returns in excess of the risk-free rate. I construct zero cost portfolios long stocks that have been sold by mutual funds in fire-sales and short in voluntary mutual fund sales. Portfolios are constructed monthly using equal and value weights. Stocks are included starting 3 months after the respective sale event and are held for 3 months after inclusion. I control for the three Fama-French risk factors, namely the return on the value-weighted market portfolio in excess of the riskfree rate, the size and value factor, and momentum. N denotes the number of monthly return observations, t-statistics are provided in parentheses.

3-month holding period											
Equally weighted						Value weighted					
Intercept	Rm-Rf	SMB	HML	UMD	R^2	Intercept	Rm-Rf	SMB	HML	UMD	R^2
1.55%	-0.18				0.01	1.78%	-0.28				0.01
(2.46)	(-1.20)					(3.11)	(-1.33)				
1.63%	-0.10	-0.43	-0.01		0.07	2.18%	0.09	-0.78	0.45		0.18
(2.61)	(-0.57)	(-2.38)	(-0.05)			(3.82)	(0.38)	(-3.28)	(1.51)		
1.10%	-0.03	-0.26	-0.06	-0.47	0.18	1.58%	-0.14	-0.59	0.39	-0.53	0.25
(1.82)	(-1.75)	(-1.46)	(-0.29)	(-3.90)		(3.15)	(-0.60)	(-2.49)	(1.36)	(-3.25)	
N =	123					N =	123				

Figure 1a: **Distribution of Flow Correlation (1990-1999)**
This figure displays the histogram of the distribution of the flow correlation measure by decade. The flow correlation coefficient is calculated as the correlation between fund's flows and the aggregated value weighted flows of all funds holding assets in the fund's current portfolio. Correlation is estimated in rolling 48 month windows, using quarterly flows for 1984-1990 and monthly flows for 1990-2008. Panel b shows the distribution of flow correlation for 1990-1999.

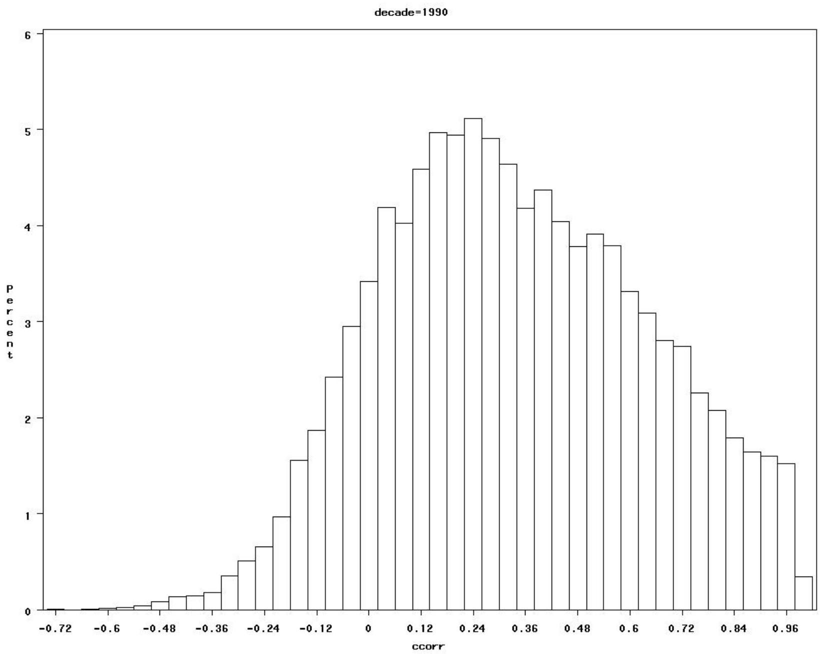

Figure 1b: **Distribution of Flow Correlation (2000-2008)**
This figure displays the histogram of the distribution of the flow correlation measure by decade. The flow correlation coefficient is calculated as the correlation between fund's flows and the aggregated value weighted flows of all funds holding assets in the fund's current portfolio. Correlation is estimated in rolling 48 month windows, using quarterly flows for 1984-1990 and monthly flows for 1990-2008. Panel c shows the distribution of flow correlation for 2000-2008.

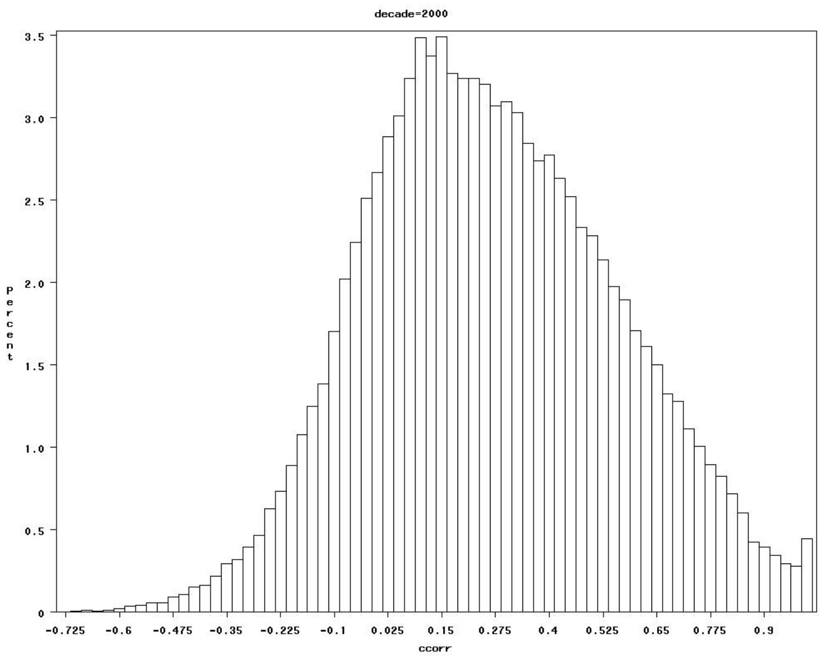

Figure 2: **Distribution of Size Factor Loading (1994-2008)**
This figure displays the histogram of the distribution of the loading on the size factor in mutual fund portfolios for 1994-2008.

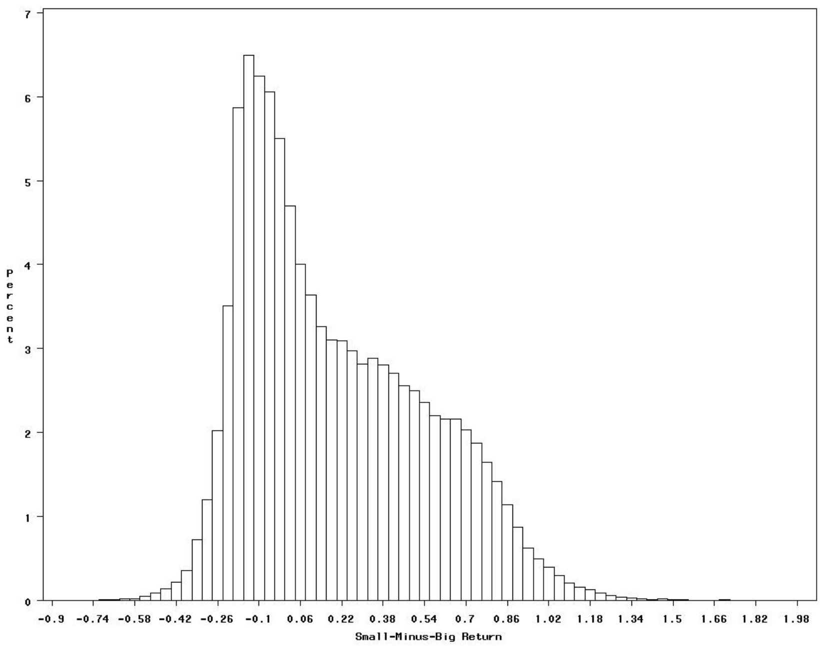

Figure 3: **Distribution of Book to Market Factor Loading (1994-2008)**
This figure displays the histogram of the distribution of the loading on the Book to Market factor in mutual fund portfolios for 1994-2008.

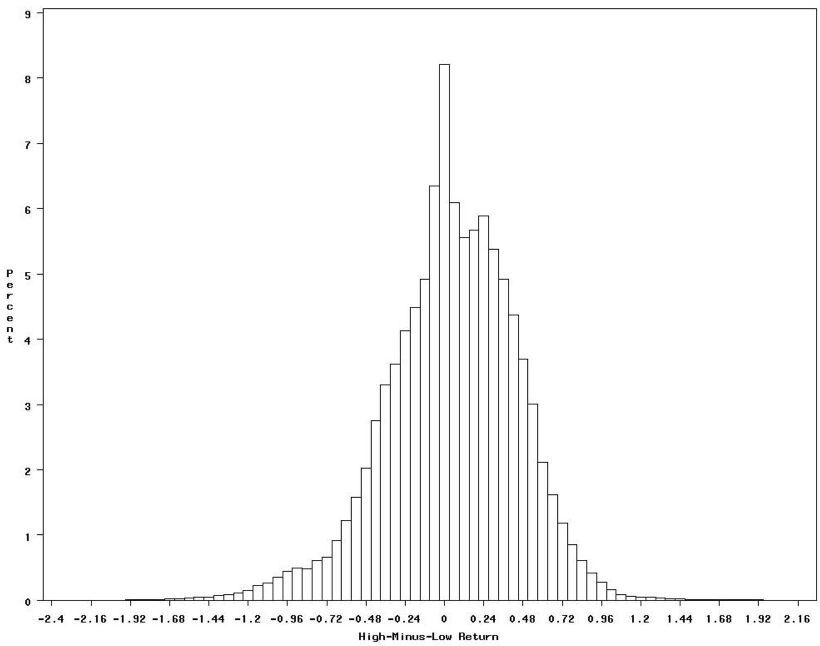

Figure 4: **Distribution of Momentum Factor Loading (1994-2008)**
This figure displays the histogram of the distribution of the loading on the Momentum factor in mutual fund portfolios for 1994-2008.

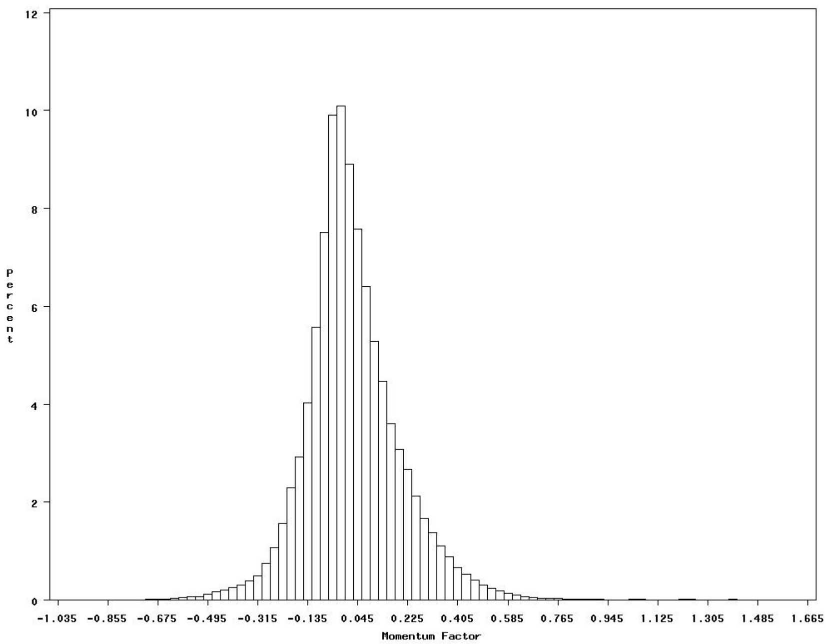

Figure 5: **Portfolio investment with trading cost**
This figure displays portfolio investment for the cross-section of assets with different liquidity cost. The x-axis represents the cross-section of assets sorted increasing in transaction cost. The y-axis represents investment for a portfolio with unit value. The dotted lines represent investment with zero transaction cost, while the solid lines are the portfolios for assets with transaction cost. Depending on variance of trading flows agents put more or less weight into the liquid (costless) portion of the portfolio

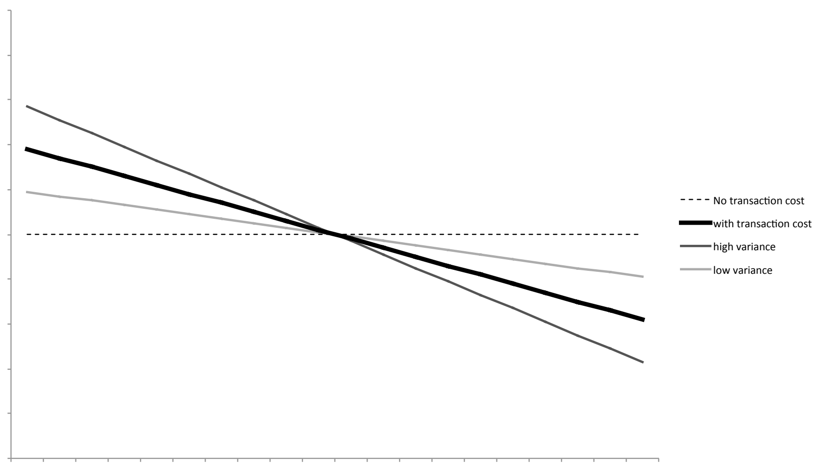

Figure 6: **Rebalancing of portfolio investment after non-zero flow**

This figure displays the change in portfolio investment with inflows/outflows for the cross-section of assets with different liquidity cost. The x-axis represents the cross-section of assets sorted increasing in transaction cost. The y-axis represents investment for a portfolio with an initial unit value. The dotted lines represent investment with zero transaction cost.

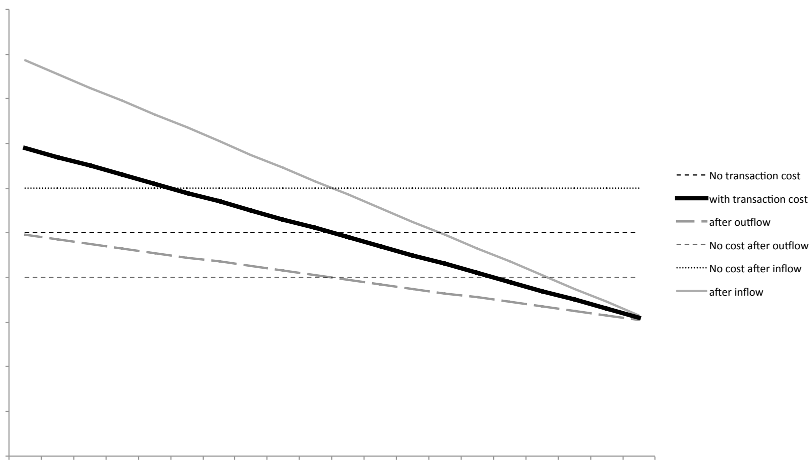

Figure 7: **Quoted Bid-Ask spread and reduced Tick size**
This figure displays the change in the quoted Bid-Ask spread for a reduction in the size of the minimum price variation (Tick).

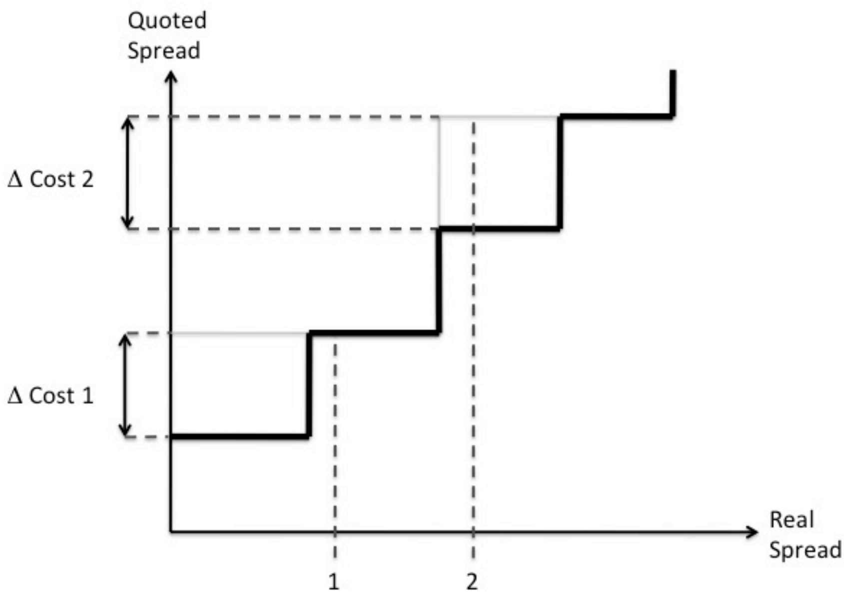

Figure 8: **Portfolio Rebalancing without Flow**
This figure illustrates the base case of trades from portfolio rebalancing in the absence of a liquidity shock.

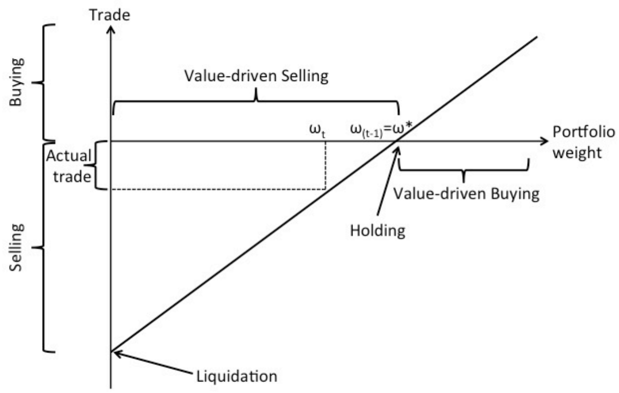

Figure 9: **Liquidity Sale with Outflow**
This figure illustrates the resulting liquidity-driven trade for post-adjustment portfolio weights between $\omega_{(t-1)}$ and ω^*.

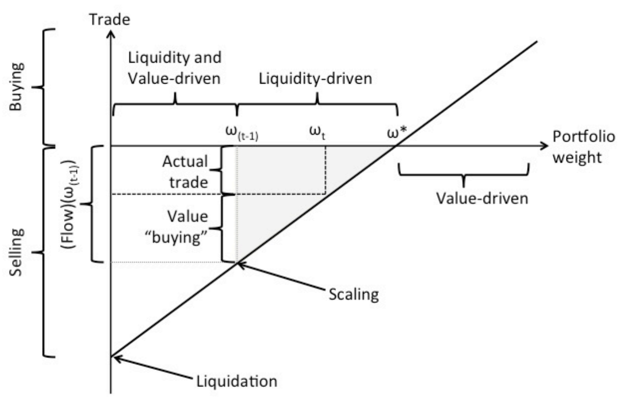

Figure 10: **Value-driven Purchase with Outflow**
This figure illustrates the resulting value-driven trade for post-adjustment portfolio weights larger than ω^*.

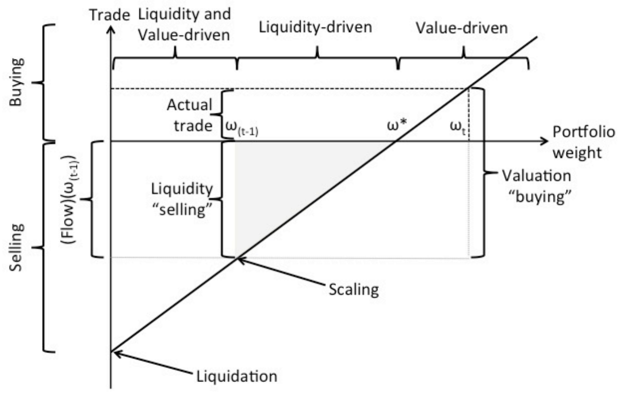

Figure 11: **Value-driven Sale with Outlow**
This figure illustrates the resulting liquidity and value driven sale for post-adjustment portfolio weights smaller than $\omega_{(t-1)}$.

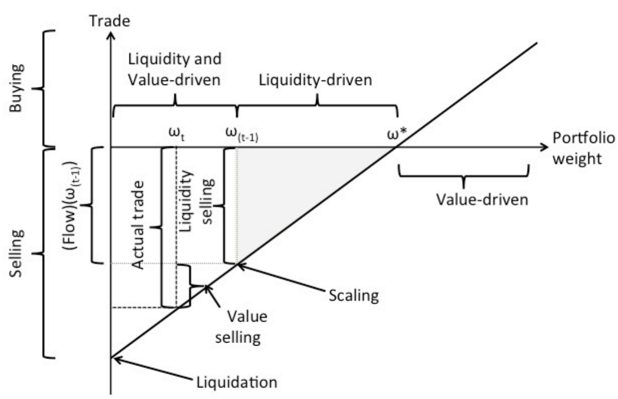

Figure 12: **Liquidity Driven Sales - Cumulative Average Abnormal Returns**
This figure illustrates the data reported in Table A.14 showing the average cumulative average abnormal returns over a single factor market model for assets being sold for liquidity reasons by distressed mutual funds according to the specification of a liquidity driven sale described in this paper. In comparison, the dashed line represents liquidity driven sales using a specification similar to Coval and Stafford (2007). The dotted vertical line represents the event month.

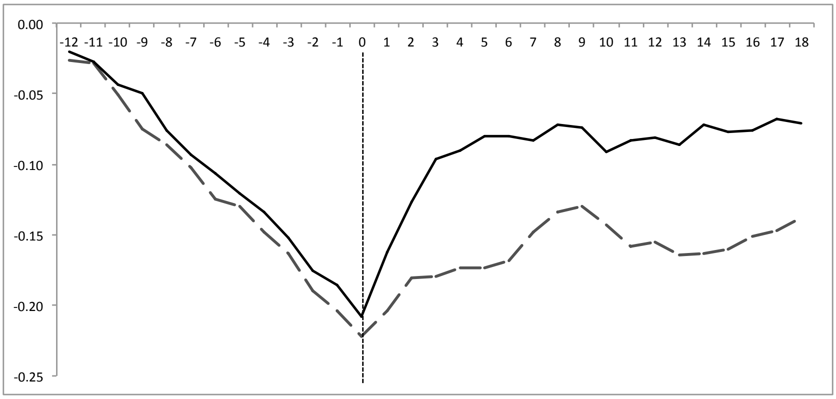

Figure 13: **Liquidity Driven Sales - Illiquidity**
This figure illustrates the normalized Amihud illiquiditiy measure for liquidity driven sales by distressed mutual funds as reported in Table A.14 . The dashed lines represent the 95% confidence interval for the mean. The vertical dotted line represents the event month.

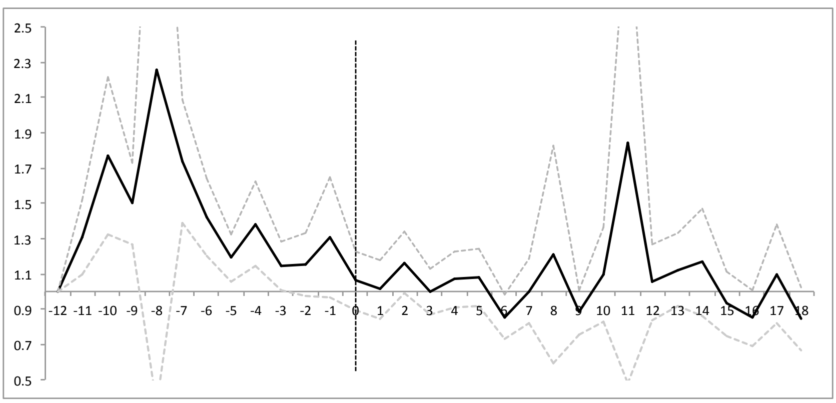

Figure 14: **Overscaling - Cumulative Average Abnormal Returns**

This figure illustrates the data reported in Table A.15 showing the average cumulative abnormal return over a single factor market model for assets being sold disproportionally by distressed mutual funds. The dotted vertical line represents the event month.

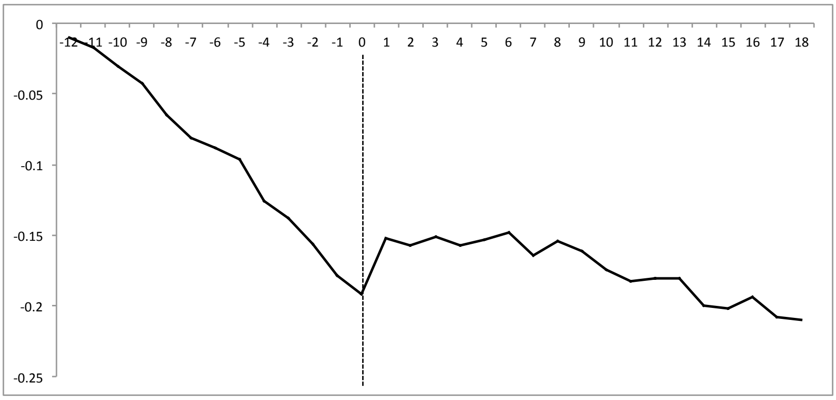

Figure 15: **Overscaling - Illiquidity**

This figure illustrates the normalized amihud illiquiditiy measure for assets being sold disproportionally by distressed mutual funds as reported in Table A.15. The dashed lines represent the 95% confidence interval for the mean. The vertical dotted line represents the event month.

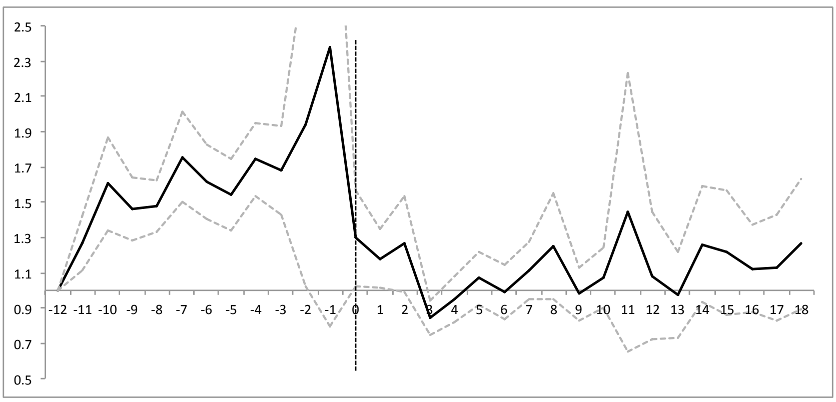

Figure 16: **Voluntary Sales - Cumulative Average Abnormal Returns**

This figure illustrates the data reported in Table A.16 showing the average cumulative abnormal return over a single factor market model for large voluntary sales by mutual funds. The dotted vertical lines represent the event quarter.

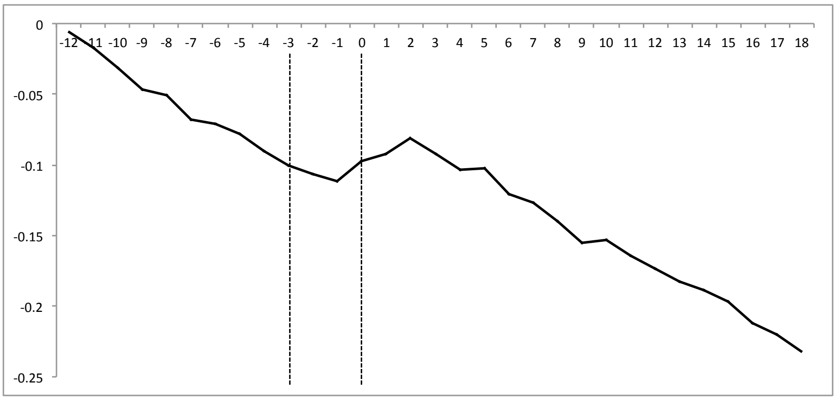

Figure 17: **Voluntary Sales - Illiquidity**

This figure illustrates the normalized amihud illiquiditiy measure for large voluntary sale by mutual funds as reported in Table A.16. The dashed lines represent the 95% confidence interval for the mean. The vertical dotted lines represents the event quarter.