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ABSTRACT

Mutual Funds and the Market for Liquidity*

We study how actively managed equity mutual funds select the liquidity level of their equity portfolio and the effects of this selection on performance. We provide evidence of five key determinants of portfolio liquidity: portfolio size, portfolio concentration, the manager's trading frequency, investment style, and fee structure. We also show that liquidity is a persistent characteristic, but it is nevertheless dynamically managed so as to offset both exogenous liquidity shocks and changes in portfolio characteristics. Liquid funds are seen to strongly overperform (underperform) during illiquid (liquid) times but, on average, net performance is unaffected by liquidity.

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"Liquidity providers ... earn returns by providing liquidity to the market ... and [liquidity buyers] know that they are giving up return" but do so to lower trading costs (Scholes, 2004).

The tremendous growth in delegated investment, most notably in equity mutual funds, has fuelled an increasing interest in the management of trading costs.[1] Theory has focused on the optimal timing and breaking of orders (e.g., Kyle, 1985, Holden and Subrahmanyam, 1992, and Huberman and Stanzl, 2003). Empirically, Chan and Lakonishok (1995) show that the trade of a typical institutional investor is broken up into smaller "package" orders, probably to reduce transaction costs. These transaction costs appear sizeable, ranging from a minimum of 1% for randomly selected NYSE firms (Holthausen *et al*., 1990) up to 8% for block trades of small firms (Keim and Madhavan, 1997).

However, the literature has rarely addressed the issue of how an investor, faced with such trading costs, chooses the level of liquidity of his portfolio. Even the recent contributions stressing the importance of liquidity in the analysis of performance (Edelen, 1999) and fee structure (Nanda *et al*., 2001) of mutual funds have not treated portfolio liquidity as a choice variable. Moreover, the fact that liquid stocks command a lower return indicates the existence of a trade-off between the costs and benefits of liquidity and suggests the existence of an optimal level of liquidity, function of the portfolio characteristics (Scholes, 2004, Lo *et al*., 2003). For example, Lo *et al.* (2003) explicitly incorporate liquidity in the traditional optimal portfolio choice problem and derive liquidity-mean-variance efficient portfolios.

In this paper, we empirically investigate whether liquidity considerations are indeed of prime importance in portfolio decisions by documenting the strength of the relation between the level of portfolio liquidity and the main portfolio characteristics. This is, to our knowledge, the first study that directly inspects the mechanism of liquidity management at the micro-level, identifying how the liquidity dimension interplays with the other objectives affecting mutual funds. In addition, by documenting an important component of the objective function of the specialized investors, this study provides important insights critical to the understanding of stock price dynamics, and in particular to the pricing of liquidity.

We focus on a panel composed of all the US actively managed equity mutual funds, as they provide an ideal testing ground. Indeed, mutual funds are sophisticated investors who demand liquidity for both a precautionary motive and a speculative motive. The precautionary motive is related to the need to meet future redemptions. The speculative motive is related to the cost of strategy implementation. For instance, managers who "time the market" need to rotate their portfolio frequently and have, therefore, to take into account the liquidity of a stock when deciding to include that stock in their portfolio. As detailed in the next section, we expect, *ceteris paribus*, the liquidity of the equity portfolio[2] to increase with its size, its concentration (i.e., the inverse of the number of stocks held), its manager's trading frequency and the liquidity of its investment style. We also expect portfolio liquidity to be a function of the policies the fund may adopt to meet its precautionary liquidity needs (e.g., cash holdings and withdrawal fees).

We first show how mutual funds choose liquidity as a function of their portfolio characteristics. Consistent with the literature on trading costs and with our working hypothesis, we find that portfolio liquidity is mainly related to portfolio size. An increase in size of a 1 standard deviation translates into an increase in portfolio liquidity of 0.16 standard deviation. The next most important variable is the manager's trading frequency. Its economic importance is about half that of size. The degree of portfolio concentration and the cash holding have an economic importance that is about a third that of size. Also, the style of the fund plays an important role in determining liquidity. For example, an aggressive growth fund has a liquidity level that is more than one standard deviation lower than that of any other equity fund.

We then gauge how "actively" funds manage their liquidity by analyzing the dynamic relationship between liquidity, portfolio characteristics and liquidity shocks over time. We adopt a dynamic panel estimation that accounts for both the endogeneity of portfolio characteristics and the unobserved heterogeneity across funds. Change in portfolio liquidity is strongly and consistently related to change in portfolio size. In particular, managers appear to react to the net positive (negative) flows in a given quarter by increasing (decreasing) their liquidity over several quarters. Moreover, managers appear to "fight" exogenous changes in their portfolio liquidity by rebalancing the portfolio so as to offset these changes, which is an indication of active management.

Finally, we focus on how liquidity affects portfolio performance and whether liquid funds underperform. On the one hand, we could expect mutual funds to "leave some alpha on the table" in order to buy liquidity. On the other hand, if the mutual fund market is competitive, liquidity should not be related to performance as, if liquid funds were underperforming, they would disappear (Berk and Green, 2004). We provide evidence that the mutual fund industry is competitive, finding that net fund performance is not related to fund liquidity unconditionally.

This, however, does not prevent liquidity from conditionally affecting performance. Indeed, consistent with Acharya and Pedersen's findings (2003) that liquid stocks tend to have superior performance in illiquid times, we find that liquid funds overperform during illiquid periods and underperform during liquid periods. The over- and under-performance is both economically and statistically significant: liquid funds (top quintile) outperform illiquid funds (bottom quintile) by 1.4% per month during the most illiquid months. The opposite holds during liquid months: liquid funds underperform by 0.8% per month during the most liquid months.

Our findings have important implications. First, they provide some understanding for the observed behavior of many institutional investors, as well as for the growing success of consulting firms – e.g., ITG and Plexus Group – which work with institutional investors to monitor and reduce their equity trading costs.

Second, our results contribute to the current debate in the literature about the price impact of liquidity. A necessary condition for liquidity to impact stock prices is that investors include liquidity into their portfolio decisions. We show that liquidity enters the portfolio optimization problem and quantify its relationship with the other main portfolio characteristics.

Third, our results are important from an equilibrium perspective. We show that, in order to cope with an increase in fund size, managers may enhance portfolio liquidity, divesting from relatively illiquid stocks and investing in more liquid stocks. At the aggregate level, this may induce an increase in the valuation spread between liquid stocks and illiquid stocks. Moreover, from a normative point of view, this suggests that a limitation in the number of stocks the funds may hold (e.g., imposed by a further segmentation of the equity styles) may increase the liquidity needs of the funds and therefore further affect valuation and liquidity spreads in the stock-markets.

Fourth, our results suggest that recent findings indicating that mutual funds perform better during bad (macroeconomic) times (Kosowski, 2002, and Lynch *et al*., 2002) could be partially or totally driven by liquidity. Given that mutual fund holdings are tilted toward liquid stocks, they should benefit from having more liquid positions than the rest of the market during bad (illiquid) times. In addition, if investors assign a positive value to good performance in bad (illiquid) times, mutual funds may actually display extra performance when an asset-pricing model using liquidity as a factor is used.

Finally, it is worth pointing out that our findings provide an additional explanation for why investors trade. Indeed, the fact that trading volumes are puzzlingly large on financial markets has induced financial economists to often question the rationale behind investors' trade. Here, we suggest that one reason is to manage portfolio liquidity.

The rest of the paper is structured as follows. In section one, we discuss and propose our working hypothesis. In section two, we describe the data treatment and the construction of liquidity proxies. We study the cross-sectional and dynamic determinants of liquidity in section three and document how portfolio liquidity affects fund performance in section four. A brief conclusion follows.

I. Hypotheses

In this section, we formulate an hypothesis about the main determinants of the equity portfolio liquidity. Recent literature on transaction costs has established two main stylized facts. First, illiquid stocks command a higher return. This higher remuneration is typically interpreted as a compensation for the higher cost of trading illiquid stocks (Amihud and Mendelson, 1986, Brennan and Subrahmanyam, 1996, Brennan *et al*., 1998, and Amihud, 2002). Second, marginal transaction costs increase with the size of the transaction (Korajczyk and Sadka, 2004). For example, Jones and Lipson (2001) show that relatively small orders face a total cost approximately equal to 0.1% of the transaction value, while large orders face a cost approximately equal to 1% of the transaction value. This suggests that a manager will select portfolio liquidity as a function of the expected cost of implementing his trading strategies. This cost is positively related to its average trade size, trading frequency and liquidity of the assets he invest in. Let us consider which observable variables allow us to proxy for these components. Construction details for all these variables are provided in the next section.

Given that we do not directly observe trade size, we can proxy for it by using portfolio size and portfolio concentration. For a fixed degree of portfolio concentration, portfolio size increases the average trade size. Similarly, for a fixed portfolio size, portfolio concentration, by limiting the manager's ability to spread trading across many stocks, increases the average trade size, while the trading frequency can be proxied by the frequency with which the manager turns over his portfolio. The liquidity of the traded assets mainly depends on the investment style of the fund. We proxy for it by separating aggressive growth funds and by constructing a variable that captures the fraction of high momentum stocks in the fund.

In the context of equity mutual funds, an important determinant of portfolio liquidity is related to the need to meet future redemptions. We call this liquidity motive "precautionary" in contrast to the "speculative" motive that is related to the cost of strategy implementation. The fund manager deals with the precautionary motive by holding cash-equivalent assets. However, as the mandate of the equity mutual fund limits the fraction of the portfolio invested in cash, just holding a fraction of the portfolio in cash might prove insufficient. In this case, the liquidity of the equity portfolio will matter because stocks will be sold to meet redemptions. We therefore expect a negative correlation between the fraction held in cash and (equity) portfolio liquidity. Similarly, everything else equal, a fund that anticipates high outflows might choose a higher level of portfolio liquidity.

Furthermore, the type of clientele, load fees and family affiliation might influence the liquidity needed for precautionary motive. For example, if a fund has many small investors, inflows and outflows are numerous, small and may partially cancel out one another. If, however, a manager has a few large institutional customers, outflows may be sizeable and less likely to net out. Therefore, the need to hold liquid positions will depend on the type of clientele. We expect a positive correlation between portfolio liquidity and the fact that the fund caters to institutional investors. The liquidity need is also related to the ability to stem redemptions. Withdrawal fees, by raising the barriers to exit, make it more costly for the fund investors to move out of the fund (see Chordia, 1996). This reduces the required degree of liquidity of the portfolio. Finally, family affiliation may impact the liquidity of the portfolio. Indeed, the trades of the funds belonging to a large family can be coordinated in order to smooth the market impact of any one of them (i.e., buying when the brother-funds are forced to sell).[3] Moreover, affiliation with a large family is likely to provide access to a better trading technology, greater expertise and cheaper brokerage services.[4]

On the basis of these considerations, we formulate the following hypothesis:

Hypothesis 1: *Portfolio liquidity should increase with portfolio size, portfolio concentration, the manager's trading frequency and the liquidity of the investment style and decrease with withdrawal fees, family size and the fraction held in cash.*

It is worth stressing that the choice of manager's trading frequency, investment style, portfolio size, portfolio concentration, the fee structure, family size as well the fraction held in cash are determined by many other additional – and often paramount – considerations. For example, the trading frequency of the manager may be affected by his investment horizon, career concerns and compensation structure. The fund style is predetermined in the fund charter and can be changed only after a lengthy procedure requiring the proxies from all the fundholders. Also, fund size is, at least partially, exogenous. Although fund families appear to limit portfolio size by closing certain funds to new investors, recent studies by Bris *et al*. (2004) and Zhao (2004) suggest that fund managers always try to maximize the amount of money under management. This would make portfolio size reasonably exogenous.[5] Regarding portfolio concentration, we note that the choice of the number of stocks to follow is related to the cost of recruiting analysts, to the size of the research department of the family to which the fund belongs to, to the charter and the scope of the fund that define the type of investment, and to the segment in which it should take place. In addition, Kacperczyk *et al*. (2004), argue that mutual funds may specialize in few stocks in order to exploit informational advantage that concentration confers. Their findings indicate that mutual funds choose concentration mainly by trading off these informational advantages and costs of under-diversification. Similarly, the fee structure cannot be readily adjusted as a function of liquidity needs. In the same way, the size of a fund family is hardly ever chosen with the sole purpose of targeting a specific liquidity level. Finally, the fraction of the portfolio held in cash is limited by the fund charter and regulations. Based on these considerations, we will start our analysis by considering fund characteristics as exogenous variables for the determination of portfolio liquidity. Then, in the second part of our study, we will allow for their potential endogeneity via the use of instruments.

If larger funds need to hold more liquid portfolios, then should we see larger funds underperform? More generally, should funds that are larger buyers of liquidity underperform? There are two alternative intuitions. On the one hand, we could expect that more liquid funds underperform the illiquid ones due to the cost of liquidity they face. This would be along the line of the literature explaining performance in terms of structural fund characteristics – e.g., hierarchy costs (Chen *et al*., 2004) – and benefits of particular strategies – e.g., concentration (Kacperczyk *et al.,* 2004).

On the other hand, if the mutual fund market is competitive, fund characteristics – i.e., liquidity – should not be related to performance. Indeed, if funds with particular characteristics were underperforming, they would disappear (Berk and Green, 2004). Moreover, while liquid mutual funds earn lower returns, still they save on transaction costs. Competitive pressure would then make them pass these savings on to the investors via lower expense ratios. The net effect would be an after-fee performance similar to that of illiquid funds. Therefore, the performance of liquid versus illiquid funds depends on the degree of competition in the mutual fund industry.

Hypothesis 2: *If the mutual fund industry is competitive, illiquid funds should not overperform the liquid funds.*

This statement about market competitiveness entails an *unconditional* relation between fund liquidity and performance, but does not give restrictions in terms of the *conditional* relation between fund liquidity and performance. Competition just requires that investors can not select funds conditioning on liquidity or other fund specific characteristics. In particular, it requires that, if the mutual fund market is competitive, investors should not be able to condition their choice of funds on the basis of their information set and the observable fund characteristics (i.e., size or liquidity).

Acharya and Pedersen (2003) find that liquid stocks tend to have superior performance in illiquid times. Given that portfolio liquidity is persistent (see next section), funds that consistently hold liquid stocks are likely to see their value appreciate more in illiquid times. We therefore expect an effect of liquidity on *conditional* performance. This cannot however be exploited by investors as they should be able to forecast liquid and illiquid times.

II. Data

A. Mutual funds characteristics

We use data from three sources. Information on stock characteristics (exchange code, share type, returns, prices, volume, shares outstanding) for the stocks listed on the NYSE, AMEX, and NASDAQ are extracted from the CRSP Stock files.[6] Information on mutual funds is derived from the CRSP Mutual Fund files. It includes the monthly (or quarterly) total net asset (*TNA*) and monthly net returns of the fund, the year the fund was organized (from which we deduce the *age* of the fund), the ICDI objective of the fund, withdrawal loads (i.e., sum of maximum deferred sales charges and redemption fees: *W-load*), expense ratio (*expense-ratio*), marketing fees (*12b-1*), fraction of TNA held in cash equivalents (from *Annual Summary Data File*) and the management family code. We also define a dummy variable, denoted as *institutional*, that takes the value of one if the fund is targeted to institutional investors and zero otherwise.[7] We construct inflows as: $In_t = TNA_t - TNA_{t-1}(1+R_t)$, where R_t is the return in month t.[8] The number of equity funds in a family is denoted by NF_t. Family size (VF_t) is the sum of TNA over all the equity funds in the family, excluding the fund of interest.

Information about the quarterly stock holdings of each fund manager (i.e., number of shares of each stock in a portfolio) is derived from the Spectrum Mutual Fund database. We define V_t as the market value of the stock holdings of the fund, n_t as the number of stocks in the portfolio, and $1/n_t$ as portfolio concentration. This database is matched with the CRSP Mutual Fund dataset.[9] The details of this procedure are reported in the Appendix. Approximately 96% (in terms of asset value) of the funds that are contained in the CRSP Mutual Fund file are matched.

We construct two variables to capture the investment style: “churning” and “momentum”. For each quarter *t,* churning ($churn_t$) is defined as the average (over the previous three quarters) sum of the shares sold and shares bought, minus the absolute value of the flows divided by twice the total net asset at quarter-end. This variable represents the frequency at which funds turn over their portfolio, or, alternatively, the inverse of their investment horizon. The momentum variable (hot_t) represents the proportion of the fund’s portfolio invested in “winner” stocks. A sock is defined as a winner if it belongs to the top 10% highest returns in the previous six months among the stocks traded on the AMEX/NYSE.[10] Given that most variables exhibit a very strong skewness, we redefine the skewed variables as $\ln(1+X)$, where $X=\{V, 1/n, NF, VF, hot, age, churn\}$.[11]

A mutual fund may enter the CRSP database multiple times if it has different share classes. Although these funds are independently listed, they have both the same pool of securities and portfolio manager and only differ in the fees they charge. Therefore, to avoid multiple counting, we consider only one fund that represents the different classes. This fund is assigned a TNA equal to the sum of the TNA of the different classes and an assigned fee equal to the average (value-weighted by TNA) fees of the different classes. This operation reduces the number of funds by 38%. We also index funds and funds without a US-equity objective (e.g., bond, precious metal, or international equity).[12]

We focus on two sub-periods: March 1983-March 1992 (P.I) and June 1992-June 2001 (P.II).[13] For the second time period, we have information on 12b-1, W-load, the style of the fund, the family owning the fund, and TNA at a monthly frequency.[14] As these additional variables are of great interest, most of the subsequent analysis is carried over P.II. Doing so, rather than considering the whole time frame, reduces the total number of observations by only 22%.

B. Liquidity

An asset is called "liquid" if it can be traded in large quantity, with a little price impact and in short period of time. Liquidity is, therefore, a multi-faceted concept that is difficult to capture with a single variable. Consequently, the empirical literature has considered several proxies for liquidity. As the existence of several well-accepted proxies open the possibility of data-snooping, we construct and use alternative measures to show that our findings are robust to the definition of liquidity.

The first and main measure is based on the "illiquidity ratio" of Amihud (2002). The illiquidity ratio for stock i during quarter t is defined as:

$$\mathrm{ILLIQ}_{\mathrm{it}} = \mathrm{Min}\left(\frac{1}{\mathrm{M}_{\mathrm{it}}}\sum_{\mathrm{d=1}}^{\mathrm{Mit}}\frac{|R_{id}|}{dv_{id}}, \frac{29.75}{0.3C_{t-1}}\right),$$

where R_{id} is the return of stock i during day d, dv_{id} is its dollar volume in millions of dollars (number of shares traded during day d times the stock price at the end of day d) and M_{it} is the number of valid observations during quarter t. C_{t-1} is the total market capitalization at $t-1$ divided by the total market capitalization at the end of July 1962.[15] The time-varying upper bound is aimed at avoiding the influence of stocks/days with a non-zero return and a very low but positive volume (see Acharya and Pedersen, 2003).

This variable is close in spirit to Kyle's λ and represents the percentage price response to a certain trading volume. Amihud (2002) provides empirical support for this measure, showing that it is positively related to high-frequency measures of price impact and fixed trading costs over the time period for which microstructure data are available. In addition, Hasbrouck (2003) shows that this measure is strongly correlated with a high-frequency estimate of Kyle's λ and concludes that, among the proxies of liquidity, "the illiquidity ratio appears to have the most reliable proxy relationship." Our analysis is mainly conducted with a quarterly "portfolio liquidity ratio" [16] based on the average (value-weighted) of the individual stock illiquidity ratios:

$$\mathrm{PLIQ}_{\mathrm{it}} = -\ln\left(\sum_{\mathrm{i}=1}^{n_{jt}} \omega_{it} ILLIQ_{it}\right),$$

where $\omega_{it} = \dfrac{N_{it}P_{it}}{V_t}$ and N_{it} is the number of shares of stock *i* that the manager holds at time *t*.[17]

Alternative measures of portfolio liquidity are based on the average daily market capitalization (*M-cap*), dollar volume (*D-volume*), turnover (*Turnover*), and stock price (*S-price*). Their construction is detailed in Appendix A.II.

In addition, we construct liquidity risk proxies as suggested by Pastor and Stambaugh (2003) (hereafter PS) and Acharya and Pedersen (2003) (hereafter AP). This provides four measures of systematic portfolio liquidity risk: the beta of PS (β^{ps}) and the three betas of AP (β^{ap2}, β^{ap3} and β^{ap4}). β^{ps} and β^{ap3} measure the co-variation between portfolio return and market-wide illiquidity. β^{ap2} measures the co-variation between portfolio liquidity and market-wide illiquidity. Finally, β^{ap4} measures the co-variation between the portfolio illiquidity and market return. We expect each beta to be negatively related to returns as investors should pay a premium to hold a security that is liquid when the market is overall illiquid, to hold a security that has high return when the overall liquidity dries out, and to hold a security that is liquid in down markets. AP and PS predict and verify empirically that stock returns are, indeed, negatively related to these betas. Their construction is also detailed in Appendix A.II.

C. Descriptive statistics

We report in Tables 1 and 2 descriptive statistics of the main variables that we use in this study. In Table 1, Panel A, we display the coefficients of correlation between the different proxies of portfolio liquidity. The correlation is calculated at the portfolio level at the end of each quarter for the period 1983-2001 and then averaged over the 74 quarters.

Proxies of the level of liquidity are highly correlated with one another, with a correlation always above 80%. For example, *PLIQ* and *D-volume* display an average correlation of 83%. The only exception is *Turnover* as it is not related to any other liquidity measure. Overall, these coefficients of correlation are very similar, though slightly larger, to those constructed at the stock level by Amihud (2002).[18]

In contrast, proxies of liquidity risk are not highly correlated with one another as the coefficients range from 1% to 36%. Proxies of liquidity risk are, nonetheless, reasonably positively correlated with proxies of liquidity level. The correlation between β^{ps} and proxies of liquidity level ranges from 9% to 13%, but the correlation is higher for the betas of Acharya and Pedersen. For example, the correlation between β^{ap2} and PLIQ is 46%. Finally, it is interesting to note that liquidity level proxies are more related to fund size than liquidity risk proxies. The coefficient of correlation ranges from 17% to 22% for liquidity level proxies and from 1% to 11% for liquidity risk proxies.

We also report the (across funds) average first order autocorrelation coefficient. Autocorrelation measures the degree of persistence of our measures of portfolio liquidity. The first order autocorrelation coefficient $\rho(1)$ is defined as: $\rho(1)=\gamma(1)/\gamma(0)$, where $\gamma(\mathrm{i}) = \frac{1}{T_1 - T_0} \sum_{\mathrm{t=T_0+i}}^{\mathrm{T_1}} (y_t - \bar{y})(y_{t-i} - \bar{y})$ and $\bar{y}$ is the average of y between time T_0 and T_1. We find that portfolio liquidity risk is persistent but not so much as the level of portfolio liquidity. The autocorrelation at the quarterly frequency of portfolio liquidity risk ranges from 53% to 65% whereas it is 81% for dollar volume and 70% for the liquidity ratio.

In Table 1, Panel B, we report the correlations between fund characteristics (e.g., size, concentration). As in Panel A, the correlation is calculated at the portfolio level over the period 1983-2001. The figures show a very high correlation between portfolio size, portfolio concentration, family size and fees. Fund size has the highest correlation with family size (46%). This indicates that only large families opt to have large funds, perhaps because they can more readily face the challenging liquidity management of such funds. Alternatively, families may be large because they have been successful at "growing a star fund." The second variable most related to portfolio size is portfolio concentration (-43%). As discussed in the previous section, we expect large funds to hold more stocks in order to reduce transaction costs. It is also interesting to note that larger funds charge lower fees. The correlation between the expense ratio and fund size is 35%. Finally, the positive relationship between fund size and churning (correlation is 25%), indicates that larger funds turn over their portfolio more often than smaller funds.

In Table 2, we report descriptive statistics of the main fund characteristics (different measures of liquidity, portfolio size, portfolio concentration, family size and number of funds per family) for the second sub-period (P.II). Statistics are broken down at the style level. Equity funds hold an average of 80 stocks, with a range that goes from 102 stocks held by the aggressive growth funds to 69 stocks held by the income funds. One possible explanation for the wide dispersion may be that aggressive growth funds focus on relatively illiquid stocks, and thus need to hold more stocks in their portfolio. It is interesting to note that the median holding is, rather, similar across styles: the median fund holds about 54 stocks. The comparison of mean and median indicates that a few aggressive growth funds hold significantly more stocks than the rest of the sample. Portfolio size also varies across styles, with income funds being four times larger than aggressive growth funds. Finally, a family, in our sample, manages, on average, $20 billion and holds 12 funds.

We also report the value-weighted average (fund-level) of the illiquidity ratio (*ILLIQ*). Aggressive growth (AG) funds have the highest potential price impact: 0.15% on average, and a median of 0.07%. In contrast, balanced growth and income, and income funds have an average price impact of 0.01% and a median price impact of only 0.002%. That is, if the median income fund were to sell $100 million worth of stocks in a day, the price impact of its trade would be 0.2%, i.e., a $0.2 million loss due to price impact. If the average aggressive growth fund were to do the same thing, the loss due to price impact would be as high as $15 million. To assess the bent for liquidity of mutual funds, we can compare these levels of illiquidity ratios with the 0.33% average illiquidity ratio reported by Amihud (2002) for all NYSE/AMEX individual stocks. This indicates that, overall, mutual funds hold significantly more liquid portfolios than the "average" investor.

D. Forecasted outflows

A manager may hold a liquid portfolio in order to accommodate daily redemptions. Therefore, expected outflows is a relevant variable for the choice of portfolio liquidity. To investigate this issue, we construct a proxy for expected outflows. We assume that, every year, fund managers use the cross-sectional observations of the previous year to infer the outflows they will face in the future. We conjecture the following simple forecasting model:

$$(1)\quad Eout_i = \Phi\left(x_i'b/\sigma\right) * x_i'b + \sigma * f\left(x_i'b/\sigma\right)$$

where $Eout_i$ represents the expected outflows for the *ith* fund, and $\Phi(.)$ and $f(.)$ stand for, respectively, the cumulative distribution function and the probability density function of a standard normal random variable. To estimate specification (1) we proceed as follows. Let us denote $\tilde{y}$ a latent variable that represents the degree of redemption pressure that faces the manager at the end of a given quarter.[19] This latent variable can be modeled as: $y_i = \sum_{t=1}^{12} flow_{it} I_{flow_{it}} \leq 0$, where $flow_{it}$ is the net flow in month t for fund i and I is a dummy variable that takes the value one (zero) in the case of an outflow (inflow). We consider quarterly updating frequency and set y as the sum of all the (monthly) outflows that occur in the subsequent twelve months.[20] Hereafter, we will refer to y as fund outflows. We further assume that: $\tilde{y}_i = y_i = x_i^{'} b + e_i$ if $\tilde{y}$>0 and $\tilde{y}$=0 otherwise. If the index $\tilde{y}$ is sufficiently high, then we will observe a strictly positive y. If the index is low, we observe that y is zero. This model is estimated by using a Tobit specification.

The estimation is made at quarterly frequency [from June 30th 1992 (end Q2-1992) to June 30th 2001 (end Q2-2001)], for a total number of 2,351 funds. We eliminate the funds that do not have 12 months of history and 12 months of valid flows afterwards. This reduces our sample size by 4%. The results are reported in Table 3. The first thing to note is that three variables stand our as predictors of future outflows: past outflows, past performance and portfolio size. A fund faced with high redemptions will continue to face high redemptions in the future. Performance negatively affects future outflows. Finally, larger funds face outflows of a larger magnitude.

The conditional correlation between realized outflows and forecasted outflows is always above 50%, implying a high forecast accuracy. This supports the effectiveness and implementability of our simple learning dynamic and shows that redemptions at a quarterly-frequency/yearly-horizon are predictable. This result is consistent with the findings of Johnson (2004), who shows that daily flows are readily forecastable.

III. The determinants of liquidity

We focus on the determinants of portfolio liquidity. We first consider the cross-sectional dimension. Then we study the dynamics of liquidity management.

A. A cross-sectional analysis

We start by estimating the following specification:

$$L_{jt} = \alpha_t + \beta_t V_{jt} + \gamma_t \,(1/n)_{jt} + \delta_t VF_{jt} + \eta_t F_{jt} + \lambda_t O_{jt} + \mu_t H_{jt} + \theta_t C_{jt} + \varepsilon_{jt}, \qquad (2)$$

where, for the jth mutual fund at the end of quarter t, L is one of the proxies for liquidity we described above, V and n are, respectively, the size and number of stocks of the fund, VF is family size, F is the vector that includes W-load, expense-ratio, dummy variables for institutional investors and aggressive growth style, and the fraction held in cash. O is the expected outflows, C stands for churn and H for hot.

Specification (2) is estimated as a series of independent cross-sections by Generalized Least Squares. We report the proportion of regressions for which the coefficient of interest is significantly positive (negative) at a 5%-level test. For comparability with the existing literature, we also report the Fama-McBeth *t-statistics*. Given that certain variables are persistent, we compute the time-series standard errors as suggested by Newey and West (1987).

The results are displayed in Table 4. In Panels A, B and C (S.1 to S.4), the dependent variable is *PLIQ*, while in Panel C (S.5 to S.8) the dependent variables are the portfolio liquidity risk proxies. Panel A is based on the entire sample period (1983-2001), while Panel B focuses on the recent time period, for which we observe more portfolio characteristic (1992-2001). In Panel C (S.1 to S.4), we eliminate time-varying style specific unobserved characteristics. To do so, we first compute the average value of each variable within each style at each point in time, using either value-weighted averages or equally-weighted averages. Then, at the end of each quarter, we subtract from each observation its corresponding style average.

The first result is the positive relationship between size and liquidity ($\beta > 0$). This holds for all portfolio liquidity (level) proxies, across all specifications and sub-samples.[21] In the case of *PLIQ*, the (Fama-McBeth) *t-statistics* of β is always above 2.6 across all specifications. Moreover, size and *PLIQ* are significantly positively related in more than 80% of the quarters. The economic magnitude of size is very stable across specifications and is higher than the economic magnitude of any other variable. An increase in size by a 1 standard deviation translates into an increase in portfolio liquidity of 0.16 standard deviation [S.8 Panel B].

The next most important variable is the manager's trading frequency. Its economic importance is about half that of size. Managers who pursue high turnover strategies restrict their investment universe to the most liquid stocks.

The degree of portfolio concentration and the cash holding have an economic importance that is about a third that of size. Their statistical significance is strong and the sign is consistent with our working hypothesis. Managers who hold a high fraction (of TNA) in cash hold an equity portfolio that is more illiquid than managers who hold a low fraction in cash. The result for portfolio concentration are as expected but could be nonetheless surprising. If holding more stocks significantly reduces liquidity needs, why are mutual funds holding an average of just 80 stocks while, just in the US, there are over 3000 stocks available? The cost of following stocks, hierarchy costs (Chen *et al*., 2004) and the benefits of concentration (Kacperczyk *et al.,* 2004) are thus likely to be sizeable in practice.

The style of the fund plays a critical role in determining liquidity. For example, an aggressive growth fund has a liquidity level that is more than one standard deviation lower than that of any other equity fund. Given the importance of style, we style-adjust all the variables in Panel C (S.1 to S.4). Such an adjustment does not change any of the previous results neither in terms of statistical significance or economic significance, with the partial exception of family size. The expected outflows are significant if considered on their own, but become insignificant once the other variables are included in the specification. As an additional robustness check, we also include the expected variance of the outflows. Indeed, it is possible that what really affects funds is the uncertainty about future redemptions as opposed to the redemption level. However, the variance of outflows is never significant in the main specification.

In contrast, both expense ratios and withdrawal fees are always significantly related to portfolio liquidity. In almost every quarter and across all specifications, funds that are more liquid have lower expense ratios. Presumably, liquid funds charge lower fees to equalize their after-fees performance to that of other funds. This would suggest that liquid funds expect to have a lower performance and choose to charge lower fees to remain a competitive investment for investors. In addition, withdrawal fees are negatively related to liquidity. We interpret withdrawal loads as a barrier to exit for investors. Such a barrier reduces the incentive of investors to redeem cash, which, in turn, reduces the need for liquid stocks.

Jones and Lipson (2001) and Keim and Madhavan (1997) find that execution costs are higher for momentum investors. To the extent that our proxy (*hot*) captures the degree of momentum trading, we expect that the higher the value of *hot*, the more liquid the portfolio should be. This prediction is also consistent with the fact that "winner" stocks are widely believed to be more liquid (Lee and Swaminathan, 2000). In fact, we observe the opposite, although the effect is not statistically significant (at a 5%-level test) when we account for fixed style effects.

Finally, institutional funds are more liquid. The portfolio liquidity of institutional funds is, *ceteris paribus*, higher than that of non-institutional funds by a 0.1 standard deviation. If a fund has many small investors, inflows and outflows are numerous, small and may partially cancel one another out. If, however, a manager has a few large institutional customers, outflows may be sizeable and less likely to cancel one another out. This constrains the manager to hold more liquid positions. This finding is also consistent with other recent findings (James and Karceski, 2003) showing that institutional funds have a weaker flow-performance relationship, which entails a lower predictability of flows, and hence a greater need to hold liquid stocks.

In Panel C of Table 4 (S.5 t0 S.8), we use liquidity betas as dependent variables. Most of the results previously described are similar for β^{ap2}, $\beta^{ap3}$and β^{ap4}. We recall that β^{ap2} measures the co-variation between portfolio liquidity and market-wide illiquidity, β^{ap3} and β^{ps} measure the co-variation between the portfolio return and market-wide illiquidity and β^{ap4} measures the co-variation between portfolio illiquidity and market return. β^{ps} is neither strongly nor consistently related to fund characteristics. Overall, liquidity risk is less related to portfolio characteristics than the other measures of liquidity are. In unreported results, we find that the results for portfolio liquidity risks are overall unstable. We interpret this as evidence that managers focus less on liquidity risk or that liquidity risk proxies are noisier, or both.

B. A dynamic panel specification

The above results are "static" as they represent a series of cross-sectional regressions and do not exploit the information contained in the time series dimension. In order to exploit this information and address certain econometric issues, we now move to a dynamic panel estimation. This exercise not only provides a useful robustness check, but it also allows us to deal with various econometric issues.

B.1. Methodology

A dynamic panel specification offers some important advantages. First, it allows us to test more complicated dynamic and behavioral hypotheses. For example, we can quantify the sluggishness of the liquidity adjustment and assess the cost of adjusting liquidity. Second, it allows us to properly account for endogeneity. Endogeneity arises from the dynamic nature of the liquidity-portfolio characteristics relationship that may entail reverse causality and the joint determination of certain variables (e.g., portfolio concentration, churning or size). A proper dynamic specification with instrumental variables eliminates potential parameter inconsistencies arising from simultaneity bias and endogeneity.

Nonetheless, the dynamic specification has some problems of its own. The existence of a lagged dependent variable, coupled with fund-specific characteristics, makes the standard panel estimation technique biased and inconsistent. We address this issue by taking first differences and then applying the instrumental GMM estimator of Anderson and Hsiao (1981). Given that in our problem it is not possible to determine, *a priori*, which variables are strictly exogenous, the quest for the correct instruments is rather complicated.[22] We, therefore, follow Arellano and Bond (1991) and use as instruments mainly the lagged values of the explanatory variables. Indeed, it can be shown that the lagged values of a predetermined – even if not strictly exogenous – variable are good instruments (Arellano and Bond, 1991, and Kiviet, 1995).[23] Finally, to control for heteroskedasticity, we use the two-step estimator proposed by Arellano and Bond (1991). The first specification that we estimate is the dynamic version of equation (2):[24]

$$(3) \qquad \Delta L_{jt} = \beta \Delta V_{jt} + \gamma \Delta (1/n)_{jt} + \delta \Delta VF_{jt} + \eta \Delta C_{jt} + \mu \Delta H_{jt} + \lambda_1 \Delta L_{j,t-1} + \lambda_2 \Delta L_{j,t-2} + u_{jt,}$$

where Δ(.) represents a change between periods *t* and *t*-1. The other variables are defined as before.[25] To reduce serial correlation and to study the time pattern of the adjustment of liquidity, we include the lags of the dependent variable. The consistency of the GMM estimator requires no serial correlation of the error terms and valid instruments. To test for these, we use two tests proposed by Arellano and Bond (1991). First, we test that the differenced error term is second order serially uncorrelated. Indeed, absence of serial correlation requires that the differenced residuals do not display second order correlation. The test is based on the standardized average residual co-variances, which are asymptotically distributed as N(0,1) under the null of no autocorrelation.

Second, we compute the Sargan test of over-identifying restrictions, which tests the overall validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process. The Sargan test is asymptotically distributed as a *Chi-square* with as many degrees of freedom as the over-identifying restrictions under the null hypothesis of the validity of the instruments. Table 5 shows that, for both tests and across different specifications, we consistently fail to reject the null hypotheses. This gives strong support to the robustness of the instrumental estimation and the validity of the chosen methodology.

Moving to a dynamic specification also raises the issue of the appropriate definition and nature of a change in liquidity. Indeed, liquidity can change for various reasons that are beyond the control of the manager. For example, it could simply happen that the liquidity of the stocks held by a passive manager drops. Nonetheless, one can argue that this still represents a genuine decrease in portfolio liquidity as the manager could alter his portfolio to avoid this drop in liquidity. The extent of this adjustment, however, depends on the cost of rebalancing the portfolio that may induce the manager not to entirely compensate these exogenous changes. We thus decompose total change in two complementary parts: involuntary change and voluntary change.

The involuntary change in portfolio liquidity is the change that results from either a change in the stock prices or a change in the liquidity levels, for the stocks that are held in the portfolio. In other words, it is the change in portfolio liquidity that would have been observed if the manager had not rebalanced his portfolio over the period. The voluntary change in liquidity is the change that directly results from the portfolio rebalancing of the manager. It represents how much the portfolio liquidity would have changed if stock prices and stock liquidity levels had not moved over the period.[26] We call the first component "involuntary change" (IC), the second component "voluntary change" (VC) and the sum of the two "total change" (TC). That is:

$$\mathrm{TC_t} = \Delta \frac{1}{V_t}\left(\sum_{\mathrm{i}=1}^{n_{jt}} N_{it} P_{it} ILLIQ_{it} \right)$$

$$= \underbrace{\frac{1}{V_t}\left(\sum_{\mathrm{i}=1}^{n_{jt}} \Delta(N_{it}) P_{it} ILLIQ_{it} \right)}_{VC_t} + \underbrace{\left(\frac{1}{V_t} \sum_{\mathrm{i}=1}^{n_{jt}} N_{it} \Delta(P_{it}) ILLIQ_{it} + \frac{1}{V_t} \sum_{\mathrm{i}=1}^{n_{jt}} N_{it} P_{it} \Delta(ILLIQ_{it}) \right)}_{IC_t}$$

Hence, we modify specification (3) and estimate:

(4) $-\ln(VC)_{jt} = \beta\Delta V_{jt} + \gamma\Delta(1/n)_{jt} + \delta\Delta VF_{jt} + \eta\Delta C_{jt} + \mu\Delta H_{jt} - \lambda_1 \ln(IC)_{jt} - \lambda_2 \ln(IC)_{j,t-1} - \mu\ln(VC)_{j,t-1} + e_{jt.}$

This specification allows us to investigate two issues: how much of the change in portfolio liquidity is due to a direct choice of the manager and how the fund reacts to exogenous changes in liquidity. The parameters λ capture the speed of adjustment to the desired level of liquidity. If the fund adjusts liquidity to an optimal target, we expect λ to be negative, whereas if there is no adjustment, λ should be zero.

B.2. The main findings

The results for specification (3) are displayed in Table 5 (S.1 to S.6). Specifications S.1 to S.3 report the overall results, and specifications S.4 to S.6 reports the style-adjusted results. The first thing to note is that the main findings of the static specification are confirmed with only the minor exception of churning, which looses significance in certain specifications. Liquidity is always positively related to both portfolio size and portfolio concentration. Portfolio concentration (1/*n*) is significant with a *t-statistic* of about 4, while fund size (*V*) has a *t-statistic* of about 2. The impact of family size is partially different from the static specification. Liquidity is consistently negatively related to family size, as we argued in our hypothesis. This suggests that our previous findings are robust to the endogenization of portfolio characteristics and to the elimination of fund fixed effects.

The second thing to note is the sluggish adjustment in liquidity. This is indicative of a significant cost of adjustment. If a fund increases liquidity by 1% over the quarter, it will keep increasing liquidity over the next 2 quarters (0.5% the following quarter, then 0.1%, *ceteris paribus*).

In fact, changes in liquidity in the previous quarters are the best explanatory variables for the current change in liquidity, with *t-statistics* well above 6 in all the specifications.

The third thing to note is the relationship between portfolio liquidity and the different sources of change in fund size (i.e., fund flows and capital gains). This analysis is reported in specification S.3, S.6 and S.9. Results show that most of the size effect is due to inflows. That is, when a fund receives inflows, it increases its liquidity, but when the fund gets larger due to capital gains, liquidity is unaffected. This indicates that, if adjusting liquidity involves some costs due to portfolio rebalancing, it is less costly to adjust liquidity by directly investing in more liquid stocks when new money flows in, rather than by rebalancing the portfolio.

Finally, we consider the different components of the change in liquidity: voluntary and involuntary. The results of the estimation of equation (4) are reported in specifications S.7 to S.9. They show that voluntary changes (*VC*) and involuntary changes (*IC*) are negatively related. This relationship measures the degree of 'activism' of the manager. The fact that the coefficient for *IC* is negative (e.g., *t-statistics* of –3.91, specification 2) suggests that managers actively react to exogenous changes in the liquidity of their portfolio. Nonetheless, this reaction is spread over several months, indicating that this practice is likely to be costly, and is quite incomplete. Indeed, for a 1% exogenous decrease of the liquidity of the portfolio, only a 0.3% voluntary increase in liquidity takes place during the same quarter. This confirms that the adjustment of portfolio liquidity is sluggish. Also, voluntary liquidity changes are strongly related to previous voluntary liquidity changes (*t-statistics* is always above 5), portfolio size and portfolio concentration. The magnitude and significance of all the coefficients of the previous specifications are unchanged. This provides additional evidence of the robustness of our findings.

All these findings suggest that managers are active in liquidity management. They adjust the liquidity of their portfolio in response to a change in their portfolio characteristics such as size or number of stocks held. This adjustment takes place over the same quarter and continues over the next two quarters. Moreover, managers actively fight exogenous changes in the liquidity of their portfolio.

IV. Liquidity and fund performance

In this section, we study whether the performance of equity mutual funds is affected by the level of portfolio liquidity. We first document performance differences between the most liquid funds and the least liquid funds and provide a direct economic magnitude of this difference. Then, we investigate the role of liquidity in predicting net fund returns in a multiple regression, testing hypothesis 2.

A. The cost of liquidity: Evidence from liquidity quintiles

We start by directly quantifying the performance loss related to being a liquid fund. We break down funds into liquidity quintiles and, within each quintile and for each month, we compute the average return (equally-weighted; both raw and adjusted with CAPM and 3 Fama and French factors). Table 6 reports the (time series) average of the difference between the return of the bottom liquidity quintile and top liquidity quintile, denoted as IML (Illiquid Minus Liquid), for the whole sample (1983-2001). This average is 0.03% per month for raw returns, –0.14% for CAPM-adjusted returns and –0.08% for Fama and French-adjusted returns. All these figures are not statistically different from zero. This suggests that the expected performance is independent of portfolio liquidity. This supports the hypothesis that the mutual fund industry is competitive. Nonetheless, as pointed out above, liquid funds charge a lower expense ratio. If we compute a gross performance (by adding back the expense ratio to net returns), illiquid funds outperform liquid funds by twice as much: 0.06% per month (non-tabulated figure). That is, before adjusting for risk and subtracting expenses, illiquid funds earn less than a 1% premium over liquid funds per year.

This independence between fund performance and portfolio liquidity is, however, a statement based on an unconditional estimation. Indeed, the average absolute value of IML is as high as 1.8% per month, which suggests a large time-variation of the impact of liquidity on performance. In section II.C., we noted that liquid funds tend to have a low β^{ap3} and β^{ps} (i.e., tend to earn higher returns when the market-wide liquidity is low). In section I, we pointed out reasons to believe that funds holding more liquid portfolios may outperform in illiquid times and underperform in liquid times. We therefore report in Table 6 the average IML for periods of high market liquidity (denoted as good liquidity times; see appendix A.II. for definition) and low market liquidity. When we report IML conditional on market liquidity, we find that fund liquidity is indeed an important determinant of fund performance. In the 50% (20%) most liquid months, IML is, on average, equal to 0.7% (0.8%). In contrast, in the 50% (20%) least liquid months, IML is, on average, equal to –0.6% (–1.4%). This means that in good liquidity times, illiquid funds significantly outperform whereas, during liquidity crises, liquid funds do abnormally well. Anecdotally, in October 1987 – one of the worst liquidity crises – funds in the top liquidity quintile outperformed funds in the bottom liquidity quintile by as much as 8% for that month alone.[27]

As a robustness check, we also use as measure of liquidity the average effective bid-ask spread, as constructed by Chordia *et al.* (2001).[28] This is based on estimations of individual stock spreads, computed using high-frequency data and aggregated across all the stocks and across all the days of the month. The data is available from 1988 and is provided from 1988 to 1992 by the Institute for the Study of Securities Markets (ISSM) and from 1993 by TAQ. For a detailed description of the methodology used to construct them, we refer to Chordia *et al.* (2001). The results are reported in Panel C. They are consistent with the ones previously described and show that in good liquidity times, illiquid funds significantly outperform in good liquidity times and underperform in bad liquidity times.

It is worth noting that when we use a three-factor adjustment, the above results are weakened.[29] This is mainly due to the fact that liquid stocks (as we defined them) are also large stocks. Hence, as liquid funds hold larger stocks and liquid (i.e., large stocks) stocks perform better during liquid times (as we directly tested), the three-factor adjustment, by construction, reduces the asymmetric performance pattern. The fact the asymmetric pattern in performance exists for raw returns, CAPM-adjusted returns and style-adjusted returns is interesting in explaining the conditional performance of mutual funds. This suggests that liquid funds do underperform most of the time and "make up their losses" during liquidity crises. Even though there is not a large difference in terms of (absolute) return, the difference in terms of conditional returns between liquid and illiquid funds is sizeable.

B. Regression analysis

The above results provide an economic quantification of the benefits and costs of liquidity measured in terms of returns. To deepen our understanding of the relationship between performance and liquidity, we move to a multiple regression analysis, in which we use several control variables to capture the other determinants of fund net returns.

We run independent cross-sectional GLS regressions with monthly fund returns as a dependent variable and various past fund characteristics as independent variables. Fund characteristics include portfolio size (*V*), portfolio liquidity (*PLIQ*), portfolio concentration (1/*n*), family size (*VF*), fees (*W-load*, *expense-ratio*, and *12b-1*), past 12-month returns, and additional characteristics (*hot*, *churn*, *institutional*, *age*). The regression is estimated for sample periods 1983-2001 and 1992-2001. Returns are either raw or adjusted for systematic risk. We also estimate a style-adjusted model and, given the results in the previous sub-section, we consider different sub-samples based on the level of market-wide liquidity. As in the previous sub-section, we rank all the months in terms of our measure of overall market liquidity and separately consider the cross-sectional regressions of the months that are ranked in the top 20%, the top 50%, the bottom 50%, and the bottom 20%.

The results are reported in Table 7, Panels A and B. Panel A contains the results for the overall period (1983-2001), while Panel B focuses only on the period 1992-2001. The findings are similar to what we obtained in the previous sub-section. In the independent cross-sections, the average *t-statistics* of liquidity is about 10% in absolute value, and liquidity is typically the most important variable to predict returns. However, its impact fluctuates widely over time. Liquidity is as often negatively related to performance as it is positively related to it. Thus, overall, liquidity has a non-significant negative impact on fund returns.

Interestingly, portfolio concentration behaves in a similar way to fund liquidity. Even if portfolio concentration is not as frequently statistically significant as liquidity, it is nonetheless statistically negatively significant in bad liquidity times and statistically positively significant in good liquidity times. Also, overall, it has a non-significant impact on fund returns. These results are robust to style adjustments and hold for both sample periods. In each specification, liquid funds strongly overperform during liquidity crises and underperform the rest of the time.

These findings suggest that, in order to improve performance in bad liquidity times, funds can either increase the liquidity of their portfolio or increase the number of stocks held. Let us quantify and compare the cost of these two alternative strategies. We denote σ_n and σ_{PLIQ} as the standard deviations of *n* and *PLIQ*, respectively. The results for the CAPM-adjusted estimation in Panel A show that during months of low market liquidity (bottom 20%), a 10 basis points increase in the excess return is obtained by either increasing the portfolio liquidity by $0.1\sigma_{PLIQ}$ or by increasing the number of stocks by $0.4\sigma_n$. In contrast, during months of high market liquidity (top 20%), a 10 basis points increase in the excess return is obtained by either decreasing the portfolio liquidity by $0.3\sigma_{PLIQ}$ or by increasing the number of stocks by $2.8\sigma_n$. This suggests that conditional performance is more sensitive to liquidity than to the number of stocks held, and shows the sizeable role played by liquidity on conditional performance.

To further assess the impact of a change in liquidity across different time periods, let us consider an increase in portfolio liquidity equal to $1\sigma_{PLIQ}$. The (monthly) excess return is expected to increase by 48 basis points during liquidity crises and to decrease by 3 basis points overall. These magnitudes are sizeable, especially if compared to analogous changes at the stock level. Brennan *et al.*

(1998) report that in the universe of NYSE/AMEX, a 1 standard deviation increase in (the logarithm of) dollar volume causes a decrease in excess return of 11 b.p. per month.[30]

In Panel C, we report the relationship between fund performance and fund βs. The results do not substantially differ from the previous ones. Performance is unrelated to fund liquidity risk unconditionally, while conditionally, funds with good liquidity properties offer a higher performance in illiquid months. The relationship between liquidity risk and performance is, nonetheless, not so strong and consistent as the relationship between liquidity level and conditional performance.

The relationship between fund size (V) and performance is also a variable of interest. Consistent with what is reported by Chen *et al*. (2004), we find that size is negatively related to performance if we include in the specification family size. However, this result is not very robust, as the coefficient is statistically significantly negative in less than 25% of the months. Nor is it economically very significant, as a 1 standard deviation increase in fund size decreases performance by a mere 0.06% per month. Chen *et al*. (2004) argue that the negative relationship between fund size and performance is due to organizational diseconomies rather than liquidity. Organizational diseconomies appear because large funds need to come up with more ideas and to hire more managers than small funds do. They propose the number of stocks held in a portfolio as a measure for this organizational cost. However, their data do not allow them to directly compute the liquidity of the fund or the number of stocks held by the fund. Our findings show that, in fact, even after controlling for liquidity (*PLIQ*) or portfolio concentration ($1/n$), the size effect is still present. In addition, neither liquidity or portfolio concentration are related to returns unconditionally.

These findings suggest that the negative relationship between size and return is not related to either the cost of higher liquidity or to the cost of holding more stocks. In addition, fund characteristics (i.e., size, liquidity, concentration) do not appear to be strong predictors of fund returns. This is consistent with the assertion that the market for mutual fund flows is competitive, and with the mutual fund model proposed by Berk and Green (2004). Skilled managers are, in equilibrium, running larger funds and hold more liquid portfolios. Hence, portfolio liquidity, while related to fund characteristics, does not help to predict performance that is, in equilibrium, equalized across funds.

V. Conclusion

In this paper, we study the determinants of portfolio liquidity. We find that the five key determinants are portfolio size, portfolio concentration, the manager's trading frequency, investment style, and fee structure. We also show that liquidity is a persistent characteristic, but it is, nevertheless, dynamically managed so as to offset both exogenous liquidity shocks and changes in portfolio characteristics. We relate liquidity to fund performance and show that liquidity does not affect fund performance unconditionally. In other words, funds that invest in liquid stocks do not display a significantly different performance from those that invest in illiquid stocks. However, conditioning on the level of market-wide liquidity, we find that liquid funds strongly overperform during illiquid periods, and strongly underperform during liquid periods.

Our findings are consistent with recent literature on the variation in fund performance over business cycles. Lynch *et al*. (2002) find that all fund types, except growth, show abnormal performance that increases during downturns. As liquidity is intimately related to business cycles (Eisfeldt, 2004) and mutual funds hold more liquid positions than the rest of the market, their result mirrors our finding that liquid funds perform better in bad times. Future research may assess whether liquidity or macroeconomic variables related to business cycles are the primary drivers of the conditional performance of equity mutual funds.

Our results also provide new directions in terms of theoretical modeling. Indeed, if mutual funds are subject to liquidity constraints or if the choice of assets in which they invest is affected by liquidity considerations, their trading strategies and their impact on prices will differ depending on the overall assets under management in the mutual fund industry. This may shed new light on the effects of the shift from direct to delegated investment on the financial markets.

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Appendix

A.I.) The merge of the datasets

Our merging procedure basically follows that of Wermers (2000). First, we perform a merge based on the ticker. The ticker is the five-digit code that is used to represent a stock or a mutual fund. A ticker is an unofficial way of representing a mutual fund, and there are no guarantees about it being unique. However, we found it to be reasonably consistent and, hence, used it as the first phase in the merger procedure. The ticker in CRSP comes from the annual summary data file. The column called ticker has the NASDAQ ticker symbol as a five-character field. In Spectrum, the ticker comes from file 8, the Fund Ticker Information file. The fund ticker symbol here is also a five-character symbol.

An important shortcoming in using tickers, though, is that they are available for the years 1999, 2000 and 2001. We then had to extrapolate the 1999 tickers to prior years, whenever possible. Nonetheless, it should be noted that some funds' tickers were changed during the course of time. Some funds had died and their tickers had been reused. Thus, the reliability of the ticker merge weakens as we move back in time before 1999.

We therefore consider a second criterion: fund name. Unfortunately, the CRSP database uses a 50-character text field for the name, while Spectrum uses a 25-character field for the name of the fund. Thus, the names are abbreviated differently in both databases. We used a "name recognition" code written in Delphi to match the names. This code was based on the idea of matching two strings. The names of the two databases were arranged beside each other, and each name was compared with every name in the other database. Certain assumptions had to be made about the way fund names are abbreviated in Spectrum. For example, for each name, the word fund is dropped in Spectrum and company is abbreviated to Co.

We then have two strings that can be compared, using the name-matching algorithm. A match of 90% or more on the two reduced strings is considered to be a good match and is accepted. This match has a lower priority than the ticker merge. This means that if there is a conflict in the merge between the name merge and the ticker merge, the conflict is resolved by considering the ticker merge as valid.

Finally, for all the other cases, as well as the ones that seemed to be dubious, we perform an "eye match" i.e., funds are manually compared. An SAS program then combines the name match and the eye match to produce a final match.

A.II.) Construction of alternative liquidity proxies

First, the alternative portfolio liquidity proxies, at the end of quarter t, are constructed as follows:

- Market capitalization: $M\text{-}cap_{jt} = \ln\left(\sum_{i=1}^{n_{jt}} \omega_{it} P_{it} O_{it}\right)$,

where O_{it} is the number of shares outstanding in millions at the end of quarter t. The intuition behind this variable is that larger companies have a smaller price impact for a given order flow and a smaller bid-ask spread (Amihud, 2002).

- Dollar volume: $D\text{-}volume_{jt} = \ln\left(\sum_{i=1}^{n_{jt}} \frac{\omega_{it}}{M_{it}} \sum_{d=1}^{M_{it}} dv_{id}\right)$

The dollar volume is used, for example, by Brennan *et al*. (1998).

- Turnover: $Turnover_{jt} = \ln\left(\sum_{i=1}^{n_{jt}} \frac{\omega_{it}}{M_{it}} \sum_{d=1}^{M_{it}} \frac{T_{id}}{O_{id}}\right)$,

where T_{id} is the number of shares of stock i traded during day d. Turnover is used, for example, by Amihud and Mendelson (1986).

- Stock price: $S\text{-}price_{jt} = \ln\left(\sum_{i=1}^{n_{jt}} \omega_{it} \min(P_{it}, 100)\right)$.

Stock price is related to the minimum tick size, which affects the minimum bid-ask spread defined as a percentage of price (Brennan *et al*., 1998).[31]

Second, the portfolio liquidity risk proxies are constructed as follows:

To construct β^{ps}, we estimate:

$$(1) \qquad R_{it} = \alpha_i - \beta^{ps} ML_t + \delta_{1iT} MKT_t + \delta_{2iT} SMB_t + \delta_{3iT} HML_t + e_{it}, \qquad t = T-1, ..., T-60,$$

where R_{it} is the excess stock return, MKT, SMB, and HML are the three Fama-French factors and ML is the liquidity factor of PS.[32]

The second set of betas is obtained by following AP. They derive a liquidity adjusted CAPM and construct three variables that proxy for three types of liquidity risk. To compute them, we first estimate the innovations in the illiquidity of individual stocks, denoted u_{it}, and the innovation in the illiquidity of the market, denoted u_{mt}. Then, we construct the three betas for each stock and each quarter as follows:

$$\beta^{ap2} = -10^3 \sum_{i=1}^{n_{jt}} \omega_{it} \operatorname{cov}(u_{it}, u_{mt}), \quad \beta^{ap3} = 10^3 \sum_{i=1}^{n_{jt}} \omega_{it} \operatorname{cov}(r_{it}, u_{mt}), \quad \beta^{ap4} = 10^3 \sum_{i=1}^{n_{jt}} \omega_{it} \operatorname{cov}(u_{it}, r_{mt}),$$

where r_{it} is the gross return of stock *i* during month *t* and r_{mt} is the gross return of the CRSP value-weighted index during month *t*. Co-variances are constructed over the previous 15 months and the four betas are computed for each stock traded on the NYSE, AMEX and NASDAQ. The quarter-end portfolio beta is the average (value-weighted) of each stock beta in the portfolio.

It is worth mentioning that in the subsequent analysis, we separate time periods on the basis of market liquidity in order to investigate certain asymmetric patterns. For this purpose, we use the innovations in market-wide illiquidity as defined above: u_{mt}.[33] Market liquidity will be classified as relatively high when u_{mt} is relatively low.

Endnotes

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[1] We use the terminologies: liquidity, total trading costs and price impact interchangeably.
[2] Throughout the paper, portfolio liquidity refers to the liquidity of the equity portfolio only.
[3] Mutual funds can do this by either directly cross-trading with one another, or placing orders in the market in coordination with the other funds. Cross-trades, while feasible, are subject to special restrictions. Rule 17a-7 of the US Investment Company Act permits transactions between mutual funds executed at the "fair value of the asset" ("independent current market price", usually last sale market price), with fair treatment of both parties (the traded asset fits the investment guidelines of the funds and no special fee or other remuneration is paid in connection with the transaction) and on condition that a record is kept.
[4] We thank E. Sirri for suggesting this to us.
[5] Notable examples of closure include Fidelity Magellan Fund in 1997, the largest mutual fund in the US and Turner Micro Cap Growth Fund in 2000, the best performer among small-cap growth funds in 1999. Zhao (2003) counts no such closures in the 1980s and 31 in 1996 alone. The high has been reached over the first four weeks of March 2000, when six well-known, well-performing, and large mutual funds closed (Tam and O'Brian, 2000). This corresponds to the time when equity funds were the largest ever.
[6] The volume for the stocks traded on NASDAQ are adjusted by multiplying it by 0.5 to account for inter-dealers trade (see Atkins and Dyl, 1997).
[7] Funds have been identified as "institutional" if they carry such a qualification (or any abbreviation of it) in their name.
[8] If X_t is a stock and not a flow, the subscript *t* means at the end of period *t*.
[9] The availability of information at the portfolio level allows us to use the value of all the stocks in the portfolio to identify US-equity funds more precisely. Thus, we further eliminate any observation for which the total net asset as reported in CRSP (TNA) is more than twice the total value of the holdings reported in Spectrum (V).
[10] We do not include NASDAQ stocks because there is no momentum effect for these stocks.
[11] Despite this transformation, some outliers are still detected. An outlier is defined as an observation, in a given cross-section, that is beyond five standard deviations away from the mean. All outliers are replaced by the threshold value (winsorized). For example, if the variable has a mean of 2 and a standard deviation of 1, observations above 7 are replaced by 7 and those below –3 by –3.
[12] Note that some of these funds, although having a bond or precious metal objective, sometimes hold more than 80% of US equity in their portfolio.
[13] We start in March 1983 in order to have volume data on NASDAQ stocks. Not taking into account the liquidity of NASDAQ stocks could severely bias our estimates of fund liquidity. The loss of quarters (before 1983) is, however, minimal as there are fewer than 200 funds before 1983, in our database.
[14] From 1992 to 2001, our merged database includes six "equity" categories: Aggressive Growth (AG), Balanced (BL), Growth and Income (GI), Income (IN), Long-term Growth (LG), and Other funds equity funds (OF).
[15] This ratio increases from one in July 1962 to about thirty in 2001. This ratio is used by Pastor and Stambaugh (2003) and Acharya and Pedersen (2003). A minimum of 15 days of strictly positive volume and valid returns are required for inclusion every month.
[16] Although this definition of portfolio liquidity seems natural, a note is in order: the liquidity of a portfolio does not depend on its size, i.e. this measure is scale independent. To gauge the importance of such a feature, let us consider an example. Let A and B be two stocks with *ILLIQ* equal to 0.1 for stock A and 0.2 for stock B. If a manager (M1) owns *x* worth of stock A, and *y* worth of stock B, our measure indicates that the liquidity of his portfolio is $PLIQ = \ln(x+y) - \ln(0.1x+0.2y)$. If another manager (M2) owns exactly twice as much of both stocks, both portfolios have the same liquidity, i.e. portfolio liquidity is scale independent. This is because the percentage cost of trading one dollar of the portfolio is the same. Nevertheless, if both managers have to liquidate, say half of their portfolio, manager M2 will probably incur both a higher total transaction cost and a higher transaction cost per dollar traded. An alternative to the above measure is thus to construct the cost of trading one percent of the portfolio rather than the cost of trading one dollar of the portfolio. However, as we are interested in the relationship between fund liquidity and size (*V*), we use a proxy for liquidity that is not directly influenced by the level of *V*. This measure is, therefore, very conservative for our study. Lo et al. (2003) adopt the same convention to define portfolio liquidity. They also discuss this "scale independent" aspect and also note that this measure does not allow for cross-effects in liquidity among securities.

[17] We take the natural logarithm to reduce the skewness and multiply by –1 to obtain a liquidity measure instead of an illiquidity measure for ease of presentation.

[18] He reports that the average annual coefficient of correlation from 1964 to 1997 between LIQ and D-volume, M-cap, S-price and Turnover of 0.7, 0.6, 0.5, and 0.1, respectively.

[19] We can imagine that $\widetilde{y}$ is an index that increases both with the magnitude of future daily outflows and with the (time) proximity of a given outflow.

[20] There are two main reasons behind our choice of a yearly frequency. First, we need enough monthly observations to build a sensible proxy of outflows. By using fewer months, the number of values for which y is zero increases dramatically, introducing noise. Second, this allows us to adopt a frequency that is homogeneous to the frequency of observations of the cash reserve of funds. This is a key variable in the analysis of the managers' reaction to redemptions and CRSP provides this information only at a yearly frequency.

[21] The results for the other liquidity level proxies are not reported but available upon request.

[22] Maybe with the exception of the age of the fund, the indication of the style it belongs to and whether it caters to institutional investors.

[23] A variable is predetermined if "current shocks are uncorrelated with past values of y and with current and past values of x, but feedback effects from the lagged dependent variables (or lagged errors) to current and future values of the explanatory variable are not ruled out" (Arellano and Honore, 2001).

[24] When a given fund has a missing value, we consider the period before and after, separately, as two different funds. For example, if fund number 2 has data from Q1-1984 to Q3-1986 then from Q1-1987 to Q3-1989, then the first series is attributed to fund 2.1 and the second to fund 2.2. The two funds are treated separately in our analysis. In addition, we keep funds that have at least 5 successive quarters of valid data.

[25] We consider the main variables and the ones that have a variation during the interval. Indeed, given that some variables are reported with yearly frequency, we cannot compute their variation.

[26] Note that this measure is a mere proxy for voluntary changes, which is, in fact, unobservable. Indeed, the manager may rebalance his portfolio for many reasons other than liquidity, and this change in holdings may misleadingly result in an apparently voluntary change in liquidity.

[27] An analysis of the relationship between returns and liquidity for the October 1987 stock market crash is provided in Amihud *et al*. (1990).

[28] We thank A. Subrahmanayam for suggesting us the use of these data and T. Chordia for providing us with these data.

[29] This is similar to what Chen *et al.* (2004) report for their studies. They find that the negative relationship between portfolio size and performance is not robust to the use of the three-factor model. They point out that it is unclear what these factors proxy for (risk or mispricing).

[30] Other magnitudes are provided by Brennan and Subrahmanyan (1996) who report an average 6.6% per annum spread between low and high stock quintiles (formed on Kyle's lambda) and by Pastor and Stambaugh (2003) who report a 7.5% p.a. spread between the two extreme deciles (formed on systematic liquidity risk).

[31] Other measures, based on microstructure data, would be the bid-ask spread (quoted or effective), transaction-by-transaction market impact or the probability of information-based trading proposed by Easley, Hvidjkjaer, and O'Hara (2002).

[32] We thank Pastor and Stambaugh for making their data available to us.

[33] We also considered a second measure of illiquidity based on the relative market illiquidity for mutual funds, denoted RILLIQ. The intuition behind this measure is that it quantifies the cost to liquidate the market portfolio for a representative equity fund. First, we define market illiquidity (MILLIQ) as the value-weighted average of the level of ILLIQ for each common stock in the CRSP database. MILLIQ thus represents the cost of selling one dollar of the market portfolio. This cost decreases over time, from 0.136 in 1983 to 0.016 in 2001. To know the average cost of liquidating a fund, we multiply MILLIQ by the average fund size at time t and obtain RILLIQ. Given that the results obtained with this measure are very similar to those reported with the innovations in market liquidity, we do not report them. However, they are available from the authors.

Table 1: Correlation matrix of fund characteristics and liquidity proxies

This table reports (time-series) average of cross-sectional coefficients of correlation. The average is taken over the 74 quarters starting with the first quarter 1983 through the second quarter of 2001. Panel A reports the correlation between (equity) portfolio size and liquidity proxies: dollar volume, market capitalization, stock price, portfolio liquidity ratio (PLIQ), turnover, the beta of Pastor and Stambaugh (2003), and the three betas of Acharya and Pedersen (2003). Panel B reports the correlation between fund characteristics include i) sum of the market value of each equity position held by the fund (Portf. size), ii) the inverse of the number of stocks held by the fund (Port. concentration), iii) the fraction of the fund held in cash at the end of the (previous) year, iv) sum of the market value of each equity position held all the equity fund in the family (except the considered fund), v) the percentage of the fund value invested in hot stocks (stocks belonging to the top 10% performer over the past six months on the NYSE and AMEX; hot), vi) the speed at which the fund turns-over its portfolio (churn), vii) expense ratio, viii) withdrawal load (sum of maximum deferred sales charges and redemption fees; W-load), and ix) the Total Net Asset of the fund as reported by CRSP. In Panel A, the average (across funds) first-order autocorrelation coefficient is reported for each variable. The definition of all the variables is in the text. All variables except the betas and fees are expressed in natural logarithms.

Panel A: Coefficients of Correlation between fund liquidity proxies and fund size

	D-volume	M-cap	S-price	PLIQ	Turnover	β^{ps}	β^{ap2}	β^{ap3}	β^{ap4}
D-volume	1.00								
M-cap	0.97	1.00							
S-price	0.90	0.89	1.00						
PLIQ	0.83	0.82	0.83	1.00					
Turnover	0.07	-0.10	0.00	-0.02	1.00				
β^{ps}	0.13	0.12	0.10	0.09	0.00	1.00			
β^{ap2}	0.44	0.44	0.47	0.46	0.05	0.05	1.00		
β^{ap3}	0.32	0.36	0.35	0.32	-0.26	-0.02	0.25	1.00	
β^{ap4}	0.36	0.35	0.36	0.36	0.06	0.03	0.36	0.18	1.00
Portf. size	0.19	0.17	0.22	0.22	0.03	0.01	0.11	0.08	0.09
Autocorrelation (1)	0.81	0.79	0.63	0.70	-0.13	0.54	0.53	0.65	0.55

Panel B: Coefficients of Correlation between main fund characteristics

	Port. size	Portf. concentration	Fraction cash	Family size	Hot	Churn	Expense ratio	W-load	TNA
Portf. size	1.00								
Portf. concentration	-0.43	1.00							
Fraction cash	-0.06	0.07	1.00						
Family size	0.46	-0.28	-0.01	1.00					
Hot	0.02	-0.03	0.03	0.04	1.00				
Churn	0.25	-0.61	-0.03	0.21	0.08	1.00			
Expense ratio	-0.35	0.27	0.15	-0.19	0.08	-0.11	1.00		
W-load	0.08	-0.04	0.01	0.16	0.04	0.05	0.39	1.00	
TNA	0.99	-0.42	-0.05	0.46	0.01	0.24	-0.34	0.08	1.00

Table 2: Descriptive Statistics – Main Fund Characteristics across Style

This table reports the (time-series) average of the mean and standard deviation of certain fund characteristics from the end of the second quarter of 1992 (Q2-1992) to Q2-2001. A first set of fund characteristics includes: i) average illiquidity ratio expressed in basis points (ILLIQ) ii) sum of the market value of each equity position held by the fund (fund size), iii) the number of stocks held by the fund iv) the number of equity funds in the family (except the considered fund) and v) the sum of the market value of each equity position held by the whole equity fund in the family (except the considered fund). A second set of fund characteristics includes liquidity risk proxies (the beta of Pastor and Stambaugh (2003): βps, and the three betas of Acharya and Pedersen (2003): βap). A third set of fund characteristics includes i) PLIQ (portfolio liquidity ratio, as defined in the text) and the logarithm of: ii) sum of the market value of each equity position held by the fund (fund size), iii) the number of stocks held by the fund, and iv) sum of the market value of each equity position held by all the equity fund in the family (except the considered fund). The statistics are reported at the style level and for the overall sample. Sector funds, utility funds and total return funds are grouped in "other funds". The average number of funds in each style is also reported. Portfolio size (*family size*) is expressed in million (*billion*) of US dollars. Variable definitions are in the text.

Original variables:	***Aggressive growth*** (AG)	***Balanced*** (BL)	***Growth and income*** (GI)	***Income*** (IN)	***Long-term growth*** (LG)	***Other funds*** (OF)	***All***
ILLIQ (mean)	15.3	0.9	0.8	1.0	2.3	3.8	4.7
(median)	6.6	0.3	0.2	0.2	0.5	1.2	0.6
Portf. size	299.3	466.6	901.4	1219.6	768.6	336.3	648.8
	89.9	64.1	153.4	135.6	127.0	91.6	111.7
Nber of stocks	102.5	72.7	87.9	68.6	72.1	60.6	79.8
	56.9	57.4	61.1	57.5	53.1	43.6	54.2
Nber funds family	9.3	10.6	10.6	14.4	11.6	23.4	12.5
	5.3	6.1	5.8	9.1	5.9	12.4	6.4
Family size	9.1	13.2	12.7	21.2	16.9	59.6	20.0
	1.3	1.7	1.8	4.0	1.4	8.1	1.9
βps (mean)	-0.39	-0.14	-0.11	-0.39	-0.07	-0.40	-0.20
(standard deviation)	*1.63*	*0.83*	*0.79*	*0.73*	*1.13*	*1.95*	*1.33*
βap2	-4.01	-0.22	-0.20	-0.27	-0.55	-0.76	-1.17
	7.17	*1.11*	*0.95*	*1.39*	*2.17*	*2.78*	*3.96*
βap3	-0.91	-0.13	-0.12	0.03	-0.32	-0.29	-0.36
	0.74	*0.39*	*0.40*	*0.33*	*0.55*	*0.96*	*0.70*
βap4	-1.11	-0.06	-0.06	-0.10	-0.17	-0.23	-0.32
	2.64	*0.31*	*0.35*	*0.63*	*0.85*	*1.06*	*1.43*
Logs of original variables:							
PLIQ (mean)	3.24	6.23	6.41	6.14	5.68	5.07	5.32
(standard deviation)	*1.76*	*1.24*	*1.25*	*1.35*	*1.57*	*1.63*	*1.90*
Portf. size	4.34	4.33	5.05	5.07	4.81	4.43	4.70
	1.69	*1.78*	*1.84*	*1.95*	*1.93*	*1.75*	*1.86*
Portf. concentration	-4.16	-4.11	-4.21	-4.10	-4.06	-3.84	-4.09
	0.81	*0.55*	*0.66*	*0.52*	*0.62*	*0.64*	*0.68*
Family size	6.34	6.87	6.44	7.41	6.37	8.20	6.69
	3.06	*2.75*	*3.20*	*2.92*	*3.42*	*3.40*	*3.30*
Number of funds	**274**	**86**	**271**	**61**	**485**	**174**	**1351**

Table 3: A Rolling Tobit Estimation for Future Outflows

This table reports the result of a Tobit estimation, in which the dependent variable is the outflow of fund *i* from the end of quarter *t* to the end of quarter *t*+4, and the set of independent variables includes various characteristics of fund *i* at the end of quarter *t*. These characteristics are the volatility of fund returns (over the previous 18 months), fund return over the previous 12 months, the age of the fund, the outflows over the previous 18 months, portfolio and family size at the end of quarter *t*. All the variables except past performance and return volatility are expressed as natural logarithms. The coefficient estimates are reported for quarters *t*=Q4-1992 and Q4-1993. Between parentheses is the corresponding *t*-statistics. A separate estimation is performed for each quarter from Q2-1992 to Q2-2001. We report the frequency of positively and negatively significant coefficients over these 37 independent cross-sectional estimations.

	End 1992	*End 1993*	…	*Frequency of significantly positive values*	*Frequency of significantly negative values*
Constant	4.66 (5.82)	3.15 (4.92)		77%	11%
Return volatility	18.72 (4.21)	-5.42 (-1.18)		46%	11%
Past performance	-5.11 (-7.28)	-2.66 (-4.61)		0%	97%
Age	-0.12 (-1.89)	-0.17 (-3.89)		0%	46%
Past outflows	0.50 (12.03)	0.51 (16.78)		100%	0%
Fund size	0.36 (7.76)	0.40 (11.33)		100%	0%
Family size	-0.02 (-1.04)	-0.02 (-1.04)		6%	16%
Nber of observations	630	768		_	_
Nber of censored observations	104	77		_	_

Table 4: Independent Cross-Sectional Regressions of Portfolio Liquidity on Fund Characteristics

This table reports the mean coefficient estimates from independent cross-sectional GLS regressions of liquidity on fund characteristics. The liquidity proxy is PLIQ in panel A and panel B, and PLIQ, βps, βap2, βap3, or βap4 in panel C (see text for definitions). Two time periods are considered: Q1-1983 to Q2-1992 and Q3-1992 to Q2-2001. For specifications S.3 and S.4, the time period is further divided into two sub-samples: the one composed of the quarters with the highest innovations in market liquidity (S.3) and the one composed of the quarters with the lowest innovations in market liquidity (S.4). The independent variables are described in Tables 1 and 2, except the three outflows variables (realized 12-month outflows, expectation and variance of 12-month outflows from rolling Tobit [Table 3]) and two dummy variables. These dummies take the value one if, respectively, the fund is marketed to institutional investors (Institutional) or if the fund has an aggressive growth style (Aggressive growth). In the style adjusted (EW-style and VW-style) estimations in Panel C, we subtract from the value of the variable the average (equally weighted or value-weighted) value of this variable for the corresponding style and quarter. This concerns specifications S.1 to S.4 in Panel C. *t*-statistics based on Newey-West autocorrelation-consistent standard errors are reported in parentheses. The percentages of positive and negative coefficients that are significantly different from zero at a 5%-level test are shown in square brackets. The average adjusted R^2 across cross-sectional regressions are also reported. The number of observations averages 1,196 for 1992-2001 and 765 for 1983-2001. All variables, except fees and dummy variables are expressed in natural logarithms. A constant is included but not reported in each regression.

Panel A

Specifications:	1983-2001; all S.1	1983-2001; all S.2	1983-2001; H-liq S.3	1983-2001; L-liq S.4	1992-2001; all S.5
Portf. size	0.22	0.32	0.29	0.35	0.22
	(4.70) [100;0]	(4.64) [100;0]	(9.67) [100;0]	(8.66) [100;0]	(3.67) [100;0]
Portf. concentration		0.54	0.68	0.88	0.35
		(4.61) [100;0]	(9.37) [100;0]	(9.36) [100;0]	(3.63) [73;0]
Hot		-0.04	-0.05	-0.05	-0.05
		(-2.25) [14;65]	(-2.88) [16;74]	(-3.14) [11;56]	(-2.90) [19;73]
Churn		0.12	0.09	0.01	0.50
		(1.15) [15;7]	(2.59) [26;5]	(0.39) [3;8]	(1.69) [19;14]
Expense ratio		-32.77	-37.01	-28.29	-43.77
		(-4.74) [0;75]	(-9.74) [0;68]	(-8.53) [0;75]	(-3.74) [0;89]
Av. adj. R^2	5%	17%	17%	17%	14%

Panel B: Relationship between PLIQ and portfolio characteristics (1992-2001)

	S.1	S.2	S.3	S.4	S.5	S.6	S.7	S.8
Outflows (realized)	0.09							
	(2.91) [61;0]							
Expected Outflows		0.17		0.09	-0.17	-0.12	-0.10	
		(3.33) [76;3]		(2.70) [31;0]	(-1.70) [6;48]	(-1.50) [6;45]	(-1.42) [12;40]	
Variance Outflows			0.72	0.31	0.07	0.11	0.07	
			(2.90) [82;0]	(2.52) [24;0]	(0.52) [15;9]	(1.22) [18;3]	(0.20) [18;3]	
Fraction cash				-3.29	-3.16	-2.31	-2.11	-1.81
				(-3.24) [0;94]	(-3.24) [0;91]	(-3.04) [0;73]	(-3.04) [0;70]	(-3.27) [0;51]
Portf. size					0.31	0.26	0.21	0.15
					(2.74) [94;0]	(3.03) [94;3]	(2.69) [82;3]	(3.70) [100;0]
Portf. concentration						0.21	0.23	0.26
						(3.18) [50;0]	(3.28) [64;0]	(3.51) [70;0]
Family size						-0.01	-0.01	-0.01
						(-1.48) [3;27]	(-1.09) [3;17]	(-1.62) [3;27]
Aggressive growth						-2.36	-2.33	-2.33
						(-3.51) [0;100]	(-3.51) [0;100]	(-3.70) [0;100]
Institutional						0.33	0.31	0.27
						(3.31) [70;0]	(3.31) [61;0]	(3.81) [46;0]
Hot						-0.02	-0.02	-0.02
						(-2.30) [21;58]	(-2.20) [21;56]	(-2.31) [21;51]
Churn						0.99	1.08	1.26
						(2.59) [40;0]	(2.72) [40;0]	(2.89) [49;0]
Expense ratio							-37.33	-39.81
							(-3.42) [0;61]	(-3.48) [0;73]
W-load							-0.08	-0.08
							(-3.12) [0;27]	(-3.12) [0;27]
Av. adj. R^2	1%	2%	2%	4%	10%	39%	41%	38%

Panel C: Style adjustment and systematic liquidity (1992-2001)

	PLIQ Style Adjusted				***Systematic Liqudity***			
	Equally Weighed		*Value Weighed*		*βps*	*βap2*	*βap3*	*βap4*
	S.1	S.2	S.3	S.4	S.5	S.6	S.7	S.8
Expected Outflows	-0.10	-0.06	-0.14	-0.08	0.01	-0.36	-0.06	-0.15
	(-1.40) [18;33]	(-0.94) [21;24]	(-1.52) [15;39]	(-0.99) [21;33]	(1.72) [36;12]	(-1.14) [3;27]	(-1.42) [9;42]	(-1.22) [0;36]
Variance Outflows	0.11	0.08	0.29	0.21	-0.02	-0.44	0.10	0.24
	(1.07) [21;6]	(0.81) [15;6]	(2.48) [30;6]	(2.18) [27;3]	(-1.60) [6;36]	(-1.20) [0;6]	(1.10) [12;3]	(1.60) [3;0]
Fraction cash	-1.91	-1.65	-2.02	-1.73	0.01	-1.55	-0.47	-0.01
	(-3.05) [0;61]	(-2.95) [0;55]	(-3.10) [0;79]	(-2.99) [0;55]	(0.81) [27;30]	(-2.12) [0;9]	(-2.02) [3;30]	(-0.02) [0;0]
Portf. size	0.23	0.19	0.22	0.17	0.01	0.44	0.05	0.17
	(2.66) [88;3]	(2.53) [70;6]	(2.46) [73;6]	(2.28) [70;6]	(0.81) [27;30]	(2.33) [70;0]	(2.23) [42;12]	(2.62) [61;0]
Portf. concentration	0.19	0.33	0.20	0.36	-0.01	0.45	0.01	0.10
	(3.34) [61;0]	(3.44) [82;0]	(3.31) [64;0]	(3.48) [88;0]	(-2.63) [0;27]	(3.01) [52;0]	(0.26) [6;0]	(2.06) [33;0]
Family size	0.02	0.01	0.02	0.01	-0.01	0.08	0.01	0.02
	(2.78) [36;0]	(1.24) [24;0]	(2.47) [27;3]	(1.86) [18;0]	(-1.96) [0;27]	(2.76) [36;0]	(2.06) [15;9]	(2.77) [3;0]
Institutional		0.23		0.23				
		(3.20) [36;0]		(3.20) [36;0]				
Hot		-0.01		-0.01				
		(-1.65) [24;42]		(-1.80) [24;39]				
Churn		1.40		1.64				
		(3.00) [52;0]		(3.08) [67;0]				
Expense ratio		-28.31		-32.84				
		(-3.28) [0;58]		(-3.47) [0;58]				
W-load		-0.05		-0.06				
		(-2.98) [0;12]		(-3.00) [0;12]				
Av. adj. R^2	9%	15%	10%	16%	4%	4%	5%	3%

Table 5: Liquidity and firm characteristics, controlling for endogeneity

This table reports the relation between change in liquidity and change in the characteristics of the fund. In specifications S.1 to S.6, the dependent variable is the first difference in PLIQ, while in S.7 to S.9, the dependent variable is the estimated voluntary change in liquidity. In S.4 to S.9, all variables are (equally-weighted) style adjusted. The independent variables include the variables described in Table 1 (all first-differenced) and i) the fund quarterly inflows, ii) the fund quarterly capital gains, iii) the previous two changes in PLIQ, iv) the contemporaneous and lagged involuntary change in PLIQ, and v) the previous voluntary change in LIQ. The estimation uses a two-step instrumental GMM. The instruments are: the two lagged levels of the dependent variable (first and second lag in S.7, S.8 and S.9, lags 4 otherwise), the lagged independent variables (first lag; portfolio size, portfolio concentration, Number of funds in the family, family size, Hot, Churn), the contemporaneous levels of: age, expense ratio, 12b-1, W-load, and institutional dummy. In specifications S.7, S.8 and S.9, the first and second lag of the involuntary changes in liquidity and the first and second lags of the level of PLIQ are added. All the variables, except inflows, capital gains, fees and the institutional dummy variable, are expressed in natural logarithms. The *t-statistics*, robust to general cross-section and time-series heteroskedasticity, are reported in parentheses. Time dummies are included in all equations. The *p-value* for the joint significance of the independent variables (excluding time dummies) is reported. The null hypothesis of the *Sargan test* is that the instruments used are not correlated with the residuals. And the null hypothesis of the *m2* test is that the errors in the first-difference regression exhibit no second-order serial correlation. Both statistics follow a *Chi-square* distribution with degrees of freedom reported between parentheses.

Specifications	S.1	S.2	S.3	S.4	S.5	S.6	S.7	S.8	S.9
VC –1							0.57	0.59	0.68
							(5.08)	(5.44)	(7.07)
IC 0							-0.28	-0.28	-0.25
							(-2.10)	(-1.99)	(-3.55)
IC –1							-0.05	-0.06	-0.02
							(-1.42)	(-1.86)	(-0.35)
PLIQ -1	0.55	0.59	0.56	0.48	0.48	0.41			
	(10.74)	(13.21)	(14.01)	(10.08)	(10.52)	(9.84)			
PLIQ -2	0.14	0.15	0.14	0.15	0.15	0.14			
	(6.65)	(7.14)	(6.63)	(6.34)	(6.47)	(6.69)			
Portf. size	0.27	0.14	_	0.35	0.22	_	0.18	0.11	_
	(2.04)	(1.99)	_	(2.07)	(2.05)	_	(2.07)	(1.98)	_
Inflows	_	_	0.01	_	_	0.01	_	_	0.01
	_	_	(2.01)	_	_	(3.04)	_	_	(3.92)
Capital gains	_	_	-0.00	_	_	-0.70	_	_	0.03
	_	_	(-0.10)	_	_	(-1.97)	_	_	(0.17)
Portf. concentration	0.58	_	0.58	0.30	_	0.30	0.46	_	0.85
	(3.76)	_	(3.78)	(3.40)	_	(3.42)	(2.04)	_	(2.53)
Family size	-0.03	-0.02	-0.03	_	_	-0.08	-0.05	-0.06	-0.03
	(-2.03)	(-2.74)	(-2.11)	_	_	(-1.59)	(-2.71)	(-2.58)	(-2.01)
Hot	0.02	0.02	0.01	-0.03	-0.02	-0.04	0.01	0.01	0.01
	(3.92)	(2.95)	(2.75)	(-1.96)	(-1.71)	(-2.07)	(1.11)	(0.53)	(0.65)
Churn	0.04	0.00	0.02	0.02	0.02	0.01	0.02	0.07	0.01
	(2.25)	(0.05)	(1.15)	(2.77)	(2.81)	(1.83)	(1.68)	(1.48)	(0.39)
Sargan test (dff)	10.7 (8)	10.2 (8)	11.0 (9)	12.9 (8)	12.8 (8)	2.4 (9)	13.4 (9)	10.5 (9)	11.1 (9)
(p-value)	0.22	0.25	0.27	0.11	0.12	0.98	0.15	0.31	0.27
Serial correlation test (p-value)	0.97	0.97	0.86	0.28	0.27	0.28	0.59	0.55	0.13
Wald test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 6: Performance of Liquid Funds and Illiquid Funds

In this table, we report the monthly return difference between illiquid funds and liquid funds (IML). In a given month, liquid funds are the funds in the top liquidity quintile and illiquid funds are the funds in the bottom quintile. IML is reported for the whole sample (222 months from April 1983 to September 2001 in Panel A and 111 months from July 1992 to September 2001 in Panel B and C) and for four sub-periods. These sub-periods are determined by sorting months according to their market-wide innovation in liquidity (see text for definition and graph 1) in Panel A and B, and their innovation in the average effective bid-ask spread in Panel C (see text for details). We consider raw returns and returns adjusted by 1-factor model (CAPM) or 3-factor model (3FF). CAPM and 3FF adjustments are operated by computing the rolling betas of a fund over the past 18 months. Returns are in percentage terms. Newey-West adjusted *t-statistics* are reported between parentheses in Panel A. Finally, we report the CRSP value-weighted market index for each sub-period in Panel A.

Panel A: 1983-2001, Market liquidity is innovation in market liquidity

		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Raw returns					
IML	0.03	-1.39	-0.55	0.72	0.77
	(0.17)	(-3.75)	(-2.96)	(2.86)	(2.91)
CAPM adj. returns					
IML	-0.14	-1.42	-0.74	0.53	0.75
	(-0.98)	(-4.30)	(-3.90)	(2.11)	(1.95)
3FF adj. returns					
IML	-0.08	-0.40	-0.24	0.11	0.13
	(-0.96)	(-3.32)	(-2.85)	(0.81)	(0.48)
Market return	1.12	-0.43	1.57	1.12	1.70

Panel B: 1992-2001, Market liquidity is innovation in market liquidity

		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Raw returns					
IML	0.18	-1.01	-0.40	0.78	1.08
CAPM adj. returns					
IML	0.07	-1.21	-0.49	0.64	1.08
3FF adj. returns					
IML	0.10	-0.17	0.09	0.11	0.17

Panel C: 1992-2001, Market liquidity is the average effective bid-ask spread

		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Raw returns					
IML	0.18	-0.57	-0.19	0.56	0.94
CAPM adj. returns					
IML	0.07	-0.78	-0.33	0.48	0.77
3FF adj. returns					
IML	0.10	-0.15	0.02	0.19	0.10

Table 7: Independent Cross-Sectional Regressions of Monthly Fund Returns

This table reports the mean coefficient estimates from independent cross-sectional GLS regressions of monthly fund returns (net of fees) on fund characteristics (measured at the end of the previous quarter). Two time periods are considered (from April 1983 to June 1992 and from July 1992 to September 2001). Returns are either raw, CAPM-adjusted or style-adjusted. CAPM adjustments are done by computing the rolling beta of a fund over the previous 18 months. The independent variables include: past twelve-month returns, sum of the market value of each equity position held by the fund (Portf. size), the inverse of the number of stocks held by the fund (Portf. Concentration), expense ratio, age (number of quarters since fund creation), the percentage of the fund invested in hot stocks (stocks belonging to the top 10% performers over the past six months on the NYSE and AMEX), the speed at which the fund turns over its portfolio (churn). In addition, panel B and panel C include as independent variables: the sum of the market value of each equity position held by the whole equity fund in the family except the considered fund (family size), a dummy variable which takes a value of one if the fund is marketed to institutional investor (Institutional), withdrawal load (sum of maximum deferred sales charges and redemption fees; denoted W-load), and the 12b-1 fee. Liquidity is the independent variable. We use PLIQ as a proxy in Panels A and B, and we use each of the four liquidity betas as a proxy is Panel C. Only the estimates of a sub-set of these variables are reported. We form four groups of months according to market-wide liquidity (see text for definition): the top 20% and top 50% most liquid months, and the bottom 50% and bottom 20% least liquid months. The mean, standard deviation, and *t-statistics* are computed within each group independently. We consider the market liquidity that corresponds to the same month for which the return is measured. (e.g., when fund returns of February 2001 are regressed on the characteristics of the fund as of December 2000, we consider the market liquidity of February 2001). In the style-adjusted (EW-style and VW-style) specifications, we subtract from the value of the variable the average (value-weighted) of this variable for the corresponding style. *t-statistics* based on Newey-West autocorrelation-consistent standard errors are in parentheses. The percentages of positive and negative coefficients that are significantly different from zero at a 5%-level test are shown in square brackets. The number of observations averages 1,196 for 1992-2001 and 765 for 1983-2001. All variables, except fees and the institutional dummy variable are expressed in natural logarithms, returns are in percentage terms and the reported coefficients are multiplied by 10.

Panel A: 1983:2001

Raw returns		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Portf. size	-0.13	-0.62	-0.28	0.03	-0.04
	(-1.43) [6;14]	(-3.45) [2;23]	(-2.09) [8;19]	(0.29) [5;10]	(-0.35) [2;13]
Portf. concentration	-0.18	-2.35	-1.31	0.96	1.37
	(-0.44) [10;20]	(-2.82) [7;34]	(-2.44) [12;30]	(1.87) [21;15]	(1.73) [29;22]
PLIQ	-0.13	2.90	1.34	-1.60	-1.62
	(-0.40) [35;37]	(4.05) [57;20]	(3.73) [42;24]	(-2.70) [28;50]	(-3.78) [31;58]
Control var.	Yes	Yes	Yes	Yes	Yes

CAPM-adjusted returns		Market Liquidity			
		Bottom 20%	Bottom 50%	Top 50%	Top 20%
Portf. size	-0.17	-0.50	-0.33	-0.07	-0.10
	(-2.21) [5;13]	(-3.46) [0;14]	(-2.83) [4;13]	(-0.64) [8;12]	(-0.72) [4;16]
Portf. concentration	-0.39	-1.77	-1.38	0.47	0.52
	(-1.06) [15;18]	(-2.85) [5;20]	(-3.08) [8;20]	(1.02) [28;20]	(0.76) [24;20]
PLIQ	-0.18	2.55	1.42	-1.42	-1.91
	(-0.95) [35;36]	(4.43) [55;18]	(4.00) [46;23]	(-2.65) [30;49]	(-3.63) [27;56]
Control var.	Yes	Yes	Yes	Yes	Yes

Panel B: 1992:2001

Raw returns		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Portf. size	-0.34	-0.64	-0.34	-0.32	-0.08
	(-3.11) [4;17]	(-2.42) [0;41]	(-2.64) [2;22]	(-2.16) [5;13]	(-0.35) [13;13]
Portf. concentration	0.05	-1.96	-0.85	1.22	2.53
	(0.54) [9;16]	(-1.65) [14;27]	(-1.54) [9;16]	(1.69) [30;21]	(2.79) [39;17]
PLIQ	-0.44	2.62	0.75	-1.61	-2.68
	(-0.87) [42;36]	(2.64) [55;27]	(1.43) [42;36]	(-2.19) [34;55]	(-2.30) [26;70]
Family size	0.18	-0.09	0.03	0.27	0.21
	(1.98) [15;4]	(-0.66) [5;9]	(0.35) [9;4]	(2.28) [21;5]	(1.02) [30;4]
Control var.	Yes	Yes	Yes	Yes	Yes

CAPM-adjusted returns		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Portf. size	-0.34	-0.47	-0.32	-0.34	-0.20
	(-3.81) [2;14]	(-3.20) [0;27]	(-3.38) [4;18]	(-2.74) [4;27]	(-1.16) [4;17]
Portf. concentration	0.07	-1.25	-0.72	0.92	1.80
	(0.44) [16;9]	(-1.95) [18;0]	(-2.04) [15;4]	(1.47) [18;27]	(2.02) [9;26]
PLIQ	-0.48	2.29	0.71	-1.65	-2.84
	(-1.17) [42;36]	(2.46) [27;59]	(1.36) [35;44]	(-2.46) [55;30]	(-2.49) [70;22]
Family size	0.14	-0.09	0.04	1.19	0.25
	(1.97) [11;5]	(-0.97) [9;9]	(0.26) [7;5]	(1.51) [13;7]	(0.85) [17;4]
Control var.	Yes	Yes	Yes	Yes	Yes

Style-adjusted returns		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Portf. size	-0.34	-0.58	-0.31	-0.38	-0.17
	(-3.61) [4;23]	(-2.76) [0;32]	(-2.90) [2;16]	(-3.10) [2;13]	(-0.96) [4;9]
Portf. concentration	0.07	-1.86	-0.85	0.98	2.00
	(0.44) [9;16]	(-1.75) [9;36]	(-1.71) [7;18]	(1.57) [30;21]	(2.45) [39;17]
PLIQ	-0.01	2.06	0.55	-1.19	-1.93
	(-1.07) [37;45]	(2.34) [50;23]	(1.22) [35;38]	(-1.89) [36;48]	(-1.94) [30;57]
Family size	0.04	-0.05	0.05	0.22	0.11
	(1.47) [9;5]	(-0.31) [5;14]	(0.68) [5;5]	(2.08) [16;5]	(0.58) [17;9]
Control var.	Yes	Yes	Yes	Yes	Yes

Panel C: 1992:2001, raw returns, systematic liquidity

		Market Liquidity			
	All	Bottom 20%	Bottom 50%	Top 50%	Top 20%
Portf. size	-0.04	0.00	-0.01	-0.07	-0.07
	(-2.43) [12;26]	(-0.04) [32;23]	(-0.83) [15;20]	(-2.96) [9;32]	(-1.74) [9;39]
Portf. concentration	-0.01	-0.10	-0.06	0.04	0.11
	(-0.20) [22;19]	(-0.76) [23;27]	(-0.99) [13;16]	(0.53) [30;21]	(1.07) [39;22]
βps	-0.06	0.12	0.01	-0.13	-0.21
	(-1.26) [25;32]	(2.24) [46;16]	(0.20) [25;29]	(-1.76) [25;36]	(-1.58) [17;39]
Family size	0.02	0	0.01	0.04	0.03
	(2.62) [17;5]	(0.03) [5;9]	(1.29) [11;4]	(2.78) [23;5]	(1.51) [30;0]
Control var.	Yes	Yes	Yes	Yes	Yes
Portf. size	-0.04	-0.02	-0.02	-0.07	-0.07
	(-2.47) [11;23]	(-0.57) [27;23]	(-1.32) [13;15]	(-2.84) [9;32]	(-1.63) [13;39]
Portf. concentration	-0.02	-0.21	-0.09	0.06	0.16
	(-0.32) [24;21]	(-1.49) [18;32]	(-1.48) [15;18]	(0.79) [34;25]	(1.62) [43;22]
βap2	0	0.08	0.03	-0.02	-0.04
	(-0.01) [31;28]	(3.52) [55;9]	(1.62) [33;18]	(-1.66) [29;38]	(-1.64) [22;43]
Family size	0.02	-0.01	0.01	0.04	0.04
	(2.41) [21;4]	(-0.53) [9;5]	(0.71) [15;2]	(2.88) [27;5]	(1.88) [30;0]
Control var.	Yes	Yes	Yes	Yes	Yes
Portf. size	-0.05	-0.02	-0.02	-0.07	-0.07
	(-2.48) [10;25]	(-0.47) [27;27]	(-1.14) [13;20]	(-2.98) [7;30]	(-1.69) [9;39]
Portf. concentration	0.00	-0.11	-0.05	0.05	0.12
	(0.02) [23;21]	(-0.88) [18;36]	(-0.91) [13;18]	(0.78) [29;27]	(1.34) [35;22]
βap3	-0.09	0.55	-0.07	-0.1	-0.2
	(-0.57) [32;34]	(2.37) [50;18]	(-0.31) [38;29]	(-0.67) [27;39]	(-1.13) [22;57]
Family size	0.02	0	0.01	0.04	0.04
	(2.76) [15;4]	(0.27) [5;5]	(1.37) [9;2]	(2.90) [21;5]	(1.72) [30;4]
Control var.	Yes	Yes	Yes	Yes	Yes
Portf. size	-0.04	-0.01	-0.02	-0.07	-0.07
	(-2.41) [14;25]	(-0.37) [32;27]	(-1.16) [16;18]	(-2.79) [11;32]	(-1.62) [13;39]
Portf. concentration	-0.01	-0.18	-0.08	0.07	0.16
	(-0.15) [23;23]	(-1.29) [18;36]	(-1.34) [13;22]	(0.92) [34;25]	(1.63) [43;22]
βap4	-0.05	0.18	0.03	-0.12	-0.16
	(-1.68) [23;33]	(3.14) [45;9]	(0.71) [25;20]	(-2.97) [20;46]	(-2.89) [9;61]
Family size	0.03	0	0.01	0.04	0.04
	(2.57) [19;5]	(-0.06) [9;5]	(1.18) [15;2]	(2.87) [23;7]	(1.72) [30;4]
Control var.	Yes	Yes	Yes	Yes	Yes

Figure 1: Plot of the time series of innovations in market illiquidity (see section II for definition)