

Can fund managers predict changes in aggregate liquidity?

Boyce Watkins¹

Abstract

Using a unique dataset and methodology, I am able to obtain more precise estimates of hybrid fund manager holdings before, during and after low liquidity months. I document evidence that hybrid fund managers are able to predict changes in equity market liquidity, and that the ability to react to these changes adds value for investors. These results hold for 4 different measures of aggregate liquidity. Additionally, it is shown that hybrid fund managers exhibit a flight to liquidity during periods in which equity market trading costs are abnormally high.

JEL Classification codes: G11, G12, G14

Key words: mutual funds, market efficiency, asset pricing, institutional investors, equity markets.

I. Introduction

Mutual fund managers are able to accurately time changes in market-wide transactions costs. I confirm this fact using a unique dataset and a variant of the style analysis of Sharpe (1992). This finding is a supplement to the timing literature, which has traditionally focused on managers' abilities to time market-wide price movements (Bollen and Busse (2001), Treynor and Mazuy (1966), Henriksson (1981), Henriksson and Merton (1981), Graham and Harvey (1996)) as well as market volatility (Busse (2001)). The literature has not, to my knowledge, investigated how fund managers react to market-wide changes in present, past and future equity market liquidity.

It is important to understand how fund managers react to changes in market liquidity for several reasons. First, there has been a recent attack on the mutual fund industry stating that fund managers are insensitive to the costs of trading incurred by investors. For example, the Mutual Fund Reform Act of 2004 (MFRA) specifically states that fund managers should reveal all costs of trading, including transactions costs, as well as information on portfolio turnover and the number of trades. "We're taking the brokerage community off the gravy train", stated Sen. Peter Fitzgerald. Second, there has been much research stating that cross-sectional variation in fund manager fees, expenses and transactions costs are leading determinants of manager success. Comer, Larrymore and Rodriquez (2004) find that fund managers with the lowest turnover and expense ratios tend to have the highest risk-adjusted returns. Carhart (1997) finds that cross-sectional variation in the cost of trading has an impact on fund manager performance. Chalmers, Edelen and Kadlec (1999) argue that mutual fund trading costs are very high and exhibit substantial cross-sectional variation. Finally, fund manager reactions to future changes in trading costs (liquidity changes) argues in favor of the idea that fund managers may indeed possess access to privileged information signals about future market-wide regime shifts.

This paper makes contributions along the following lines. First, I use a unique dataset to introduce a technique that allows researchers to more accurately observe fund manager behavior over short horizons. More direct observance of trading patterns over short horizons serves as a solid supplement to inferences with quarterly data. If herding takes place over short horizons, this methodology and dataset may be more likely to find it. Second, I provide insights into whether managers trade in reaction to major market liquidity changes, the degree of cross-sectional variation in response to these changes, and how managers react before, during and after major changes in market liquidity.

¹ Assistant Professor of Finance, Department of Finance, Whitman School of Management, Syracuse University, USA. I would like to thank Vaneesha Boney, George Comer, Bill Francis, Norris Larrymore, Javier Rodriquez and Ravi Shukla. I would also like to thank seminar participants at Syracuse University for valuable feedback.

A flight to liquidity is documented for hybrid fund managers, supporting the conclusions of Porter (2003) for all investors in equity markets, both individual and institutional. This is the first time such flight has been documented for hybrid fund managers, or mutual fund managers in general. The use of high frequency data and constrained optimization techniques allows for a more direct window to fund manager behavior. Through this window, I am able to supplement the results of studies that use percentage of institutional ownership to infer the effects that fund managers have on equity markets. Dennis and Strickland (2003), for example, use the percentage of institutional ownership as a predictor of the stock's return during major market swings. They argue that the price patterns of stocks with high institutional ownership reveal the trading habits of institutional investors. While this is not meant to criticize in the least, it is difficult to determine if the evidence is circumstantial in nature, and not due to the absence of correlated omitted variables. Having a more direct method of inference can provide additional confidence that the results found in this kind of work are causal in nature and not correlational.

Chalmers et al. (1999) is the only paper, to my knowledge, that has worked to directly estimate the trading costs of fund managers. The work uses quarterly data to analyze the level of trading costs incurred by fund managers, and the degree of cross-sectional variation. I support this work by showing how fund managers react to changes in market-wide trading costs, and also highlighting their timing ability. Rather than estimate the trading costs themselves, I focus on a subset of fund managers that have the ability to leave equity markets all together. Also, my method allows us to see how holdings change on a month-to-month basis.

The paper is organized as follows. Section II presents theoretical motivation, section III presents initial style analysis results, section IV presents liquidity tests, and section V concludes the paper.

II. Theoretical motivation

To make inferences regarding changes in fund manager holdings, a variant of the methodologies of Sharpe (1992) and Ibbotson (1996) is used. The manager's return during any month t is decomposed as the difference between the realized return and a passive return. The passive return is argued to be the return the fund manager would have earned had the fund simply maintained the cash, stock and bond holdings from the previous month. So, let's assume that a manager possesses month $t-1$ asset holdings in k asset classes. His month t passive return is given as:

$$r_{pt} = \sum_{i=1}^k b_{pi} r_{it}. \quad (1)$$

Here, I measure the month t attribution return as the difference between the realized return and the return of a passive portfolio:

$$r_t^a = r_t - \sum_{i=1}^k b_{pi} r_{it}. \quad (2)$$

One problem with the use of Sharpe's style analysis is that fund holdings are only reported quarterly. Hence, the estimation of portfolio holdings using low frequency data would impose unduly restrictive theoretical assumptions on the analysis. Additionally, the holdings, as presented above, could be negative or exceed one, allowing for leverage use exceeding that which is available to hybrid fund managers. These problems are overcome here in two ways: First, daily data are used for the estimation, dramatically increasing the observational frequency. Through the use of daily data and constrained Ordinary Least Squares regressions, I obtain meaningful estimates of fund holdings for a cross-section of hybrid mutual funds. Hence, I only assume that holdings are constant for a month, rather than assuming they are constant over the course of several years, as would be required with quarterly (or even monthly) reporting of fund holdings. Second, I constrain the coefficients to be between 0 and 1, with the sum of the coefficients being equal to 1. This assumption fits industry practice, since most hybrid funds are not allowed to engage in

non-linear trading strategies. Our sample only contains funds adhering to this standard. The availability of such meaningful constraints allows economic theory to guide the econometric estimation, thus leading to a more precise methodological inference.

To estimate the index holdings, the following multivariate linear regression model is run, using daily data:

$$r_{pt} = \sum_{i=1}^k b_{pi} r_{it} + e_{it}, \quad (3)$$

where

- r_{pt} = total return of fund p on day t ;
- b_{pi} = exposure of fund p to asset class i ;
- r_{it} = total return of asset class i on day t ;
- e_{it} = unexplained component of fund return.

I then solve the following constrained optimization problem in order to solve for minimum variance holdings:

$$\begin{aligned} \min \quad & \left[\text{var} \left(r_{pt} - \sum_{i=1}^k b_{pi} r_{it} \right) \right] \\ \text{subject to} \quad & \\ & 0 \leq b_{pi} \leq 1 \quad \forall i \\ & \sum_{i=1}^k b_{pi} = 1. \end{aligned} \quad (4)$$

In addition to the obvious advantage of allowing for more precise tracking of fund manager holdings, the methodology allows for a firm-specific, time-varying construct of the passive portfolio. These style regressions are run for every fund and every month in the sample to obtain estimates of monthly style holdings for each fund in the sample. While the fund estimates themselves are noisy, the cross-sectional averages, as employed here, are even more precise than those used in previous studies.

Comer (2003) is the first to more carefully study hybrid fund managers in this context, but he does not use daily data. Comer, Larrimore and Rodriquez (2004) use daily data and apply this methodology, but they do not adjust the methodology to account for liquidity-based trading decisions as I do here. Additionally, their application of this technique leaves their results open to the critique that attribution returns do not properly adjust for risk. Our revised methodology not only accounts for liquidity risk, which is priced (Pastor and Stambaugh (2003)), but I also derive a decomposition of attribution returns that accounts for deliberate risk-adjustments on the part of the fund manager. Blake, Elton, and Gruber (1993) use style analysis to estimate holdings in bond funds, and they find that the technique is verified to work very well when attempting to estimate actual fund holdings. This fact is further verified in Comer et al. (2004). Fung and Hsieh (1997) and Brown, Goetzmann, and Park (2000) extend the methodology to apply it to a sample of hedge funds.

As mentioned earlier, I adjust the methodology here to account for a liquidity factor. The assumption in the methodology is that the adjustment for liquidity is homogeneous across fund managers, which allows for more precise estimation of the coefficients. Obviously, there is cross-sectional variation in fund manager behavior, but the goal here is to look for general trends and patterns. This form of inference overcomes the problem of estimating too many parameters with only 21 daily values (trading days) for each month.

I account for liquidity here as follows. Assume that the above model is altered in the following way:

$$r_{pt} = \sum_{i=1}^k b_{pi} r_{it} + e_{it} \quad (5)$$

$$st$$

$$b_{pi} = \delta_i + \lambda_i L_t,$$

where λ is the liquidity coefficient and L is the chosen liquidity measure (to be discussed below). This model is a simple conditionalization of fund manager holdings in each asset class as a function of market-wide liquidity. Such inference allows one to observe not only how fund managers trade on average, but also how they trade in response to market-wide liquidity changes. Additionally, the liquidity variable can be altered to determine how managers trade *after* major changes in liquidity have occurred, as well as determine if managers are able to *predict* major changes in market liquidity.

A. Index models

Two separate multi-index models are used here to determine attribution returns for these funds. Attribution returns are not the only measure of performance however, since later parts of the paper detail a decomposition of attribution returns that provides a more precise risk adjustment of fund manager returns.

The first model is based on the work of Comer (2003). It is a highly detailed constrained factor-loading scheme, which extends conventional models to account for the wide variety of bond and stock indices available to fund managers. 10 indices are used (described below), which more sufficiently span the investment options of a typical hybrid fund manager. The 10-index model is presented below:

$$r_i = b_{i,sp} r_{sp} + b_{i,sm} r_{sm} + b_{i,gr} r_{gr} + b_{i,va} r_{va} + b_{i,lg} r_{lg} + b_{i,sh} r_{sh} + b_{i,hq} r_{hq} + b_{i,lq} r_{lq} + b_{i,mt} r_{mt} + b_{i,tb} r_{tb}, \quad (6)$$

where

| | |
|----------|---|
| r_i | = total return for fund i ; |
| r_{sp} | = return on the S&P 500 index; |
| r_{sm} | = return on a small stock portfolio; |
| r_{gr} | = return on a growth stock portfolio; |
| r_{va} | = return on a value stock portfolio; |
| r_{lg} | = return on a long maturity bond portfolio ; |
| r_{sh} | = return on a short maturity bond portfolio; |
| r_{hq} | = return on a high quality bond portfolio; |
| r_{lq} | = return on a low quality bond portfolio; |
| r_{mt} | = return on a mortgage backed securities portfolio; |
| r_{tb} | = return on a cash (Treasury bill) portfolio. |

The stock components of fund holdings are represented by the CSRP valued weighted S&P 500 Index. The small, growth and value portfolios are created as in Fama and French (1993). All bond indices are those available from Lehman Brothers. The long maturity bond portfolio is given by the long maturity government/credit bond index. The 1-3 year bond returns come from the short maturity bond index. The low quality bond index comes from the index on high yield bonds. The cash component is the 90-day t -bill return on Datastream. The short-coming of the model is that while estimating 10 coefficients with 21 observations might provide a very high r -square¹, the noise in individual coefficient estimates and potential multicollinearity problems reduces the likelihood that the holdings have been measured precisely. Therefore, a more aggregated

¹ They only focus on the r -square, rather than the adjusted r -square. This can cause a problem in the fact that the r -square automatically increases when one includes more variables. Also, the r -square as a variance decomposer is problematic when there is no constant term (Greene, 2000).

3-factor model is also used to supplement the results, and the key conclusions here are supported in both contexts.

For robustness, a second method is used to obtain attribution returns. In the second case, 3 indices are used, rather than 10. This is the measure that I focus on in this paper, since the gain of a more refined set of estimates is outweighed by the problems of estimating so many additional parameters. So, while I am not able to determine which subclasses of stocks and bonds managers move into during low liquidity months, I have a better opportunity to gain meaningful inference regarding how they move between general asset classes.

The 3-index model is presented as follows:

$$r_i = b_{i,stock} r_{stock} + b_{i,bond} r_{bond} + b_{i,cash} r_{cash}, \quad (7)$$

where

r_{stock} = total return on the CRSP value weighted stock index;

r_{bond} = total return on the Lehman government/corporate bond index;

r_{cash} = Treasury bill returns;

Regressions are run for every fund/month, leading to 9,502 regressions in total. The focus is on cross-sectional averages of the coefficient estimates, and how they change as a function of equity market liquidity.

Measures of aggregate liquidity

Liquidity is difficult to define, although it is widely considered to be a strong determinant of market quality. For my purposes, I define liquidity as the ease with which a given quantity of an asset can be converted to cash, in a given amount of time, with minimal price concession. Such a definition measures liquidity across three key variables: time, price and quantity. The literature has many measures of market-wide liquidity. The ones chosen here involve the following factors: bid/ask spreads, short-horizon price reversals, the economic value of trading volume, and contemporaneous price impact of trade.

The model of Campbell, Grossman and Wang (1993) uses signed trading volume as the determinant of liquidity effects. The authors assume that the excess return on a given security and its order flow are jointly normally distributed, and that the conditional return on the stock for the following period is a function of the previous period's price and signed trading volume. A brief version of the argument is as follows: providers of liquidity (i.e. market makers or those taking the other side of a trade) demand high expected returns in exchange for providing their service. These higher expected returns (presuming future cash flows remain constant) show themselves in the form of contemporaneous price concessions. Such price concessions are reversed in the following days, as the price returns to its fundamental value. Such reversals predict negative short-horizon autocorrelation in stock returns. The fact that future cash flows are presumed to remain constant is an artifact of the assumption that the trades are liquidity-based, and not based on information. The reversal of the initial price movement also serves as confirmation that the risk of the security has remained constant as well. Mathematically, this can be presented as:

$$E(Q_{t+1} | Q_t, V_t) = \phi_1 Q_t - \phi_2 \tanh(\phi_3 V_t Q_t) V_t, \quad (8)$$

where Q_t is the day t excess return on the stock, and V_t is the trading volume on day t .

The equation above can then be approximated by

$$E(Q_{t+1} | Q_t, V_t) = \phi_1 Q_t + \phi_2 \text{sign}(Q_t) V_t. \quad (9)$$

Pastor and Stambaugh (2003) use the theoretical work of Campbell, Grossman and Wang (1993) to construct empirical proxies of aggregate market liquidity. They measure market-wide liquidity for stock i in month t with the following OLS regression:

$$r_{i,d+1,t}^e = \phi_{i,t} + \varphi_{i,t} r_{i,d,t} + \gamma_{i,t} \text{sign}(r_{i,d,t}^e) V_t, \quad (10)$$

where $r_{i,d,t}$ is the total return on stock i on day d in month t , $r_{i,d,t}^e$ is the return in excess of the value-weighted return on the market, and V_t is the dollar volume for stock i on day d in month t . The coefficient on signed dollar volume, $\gamma_{i,t}$, is the chosen liquidity measure for the given security. It is negative on average, since ceteris paribus, higher dollar volume should lead to a greater price reversal the following day.

P-S use the cross-sectional average of this measure each month to determine market wide liquidity. This is given by

$$\hat{\gamma}_t = \frac{1}{N_t} \sum_{i=1}^N \hat{\gamma}_{it}. \quad (11)$$

The value of $\hat{\gamma}_t$ can be considered to be the liquidity cost of trading \$1 million in stock. P-S argue that since the meaning of a \$1 million trade has changed through time, the price series should be scaled to account for changes in inflation. Therefore, a scaled series $\left(\frac{m_t}{m_1}\right) \hat{\gamma}_t$ is used

where m_t is the total dollar value at the end of month $t-1$ of all stocks in the cross-section, and the base month is August, 1962.

As it stands, the methodology can provide a return component introduced to the liquidity series through the scaling factor. In order to avoid this problem, a differenced series is used, in which the variable is first differenced, and then scaled. Innovations in aggregate liquidity are calculated as the scaled monthly difference in liquidity measures, as averaged across all stocks in the cross-section.

$$\Delta \hat{\gamma}_t = \left(\frac{m_t}{m_1}\right) \left(\frac{1}{N_t}\right) \sum_{i=1}^N (\hat{\gamma}_{it} - \hat{\gamma}_{i,t-1}). \quad (12)$$

At this point, the monthly change in the coefficient is regressed on a lag and the lagged value of the scaled level series as follows:

$$\Delta \hat{\gamma}_t = \alpha + \beta \Delta \hat{\gamma}_{t-1} + c \left(\frac{m_{t-1}}{m_1}\right) \hat{\gamma}_{t-1} + u_t. \quad (13)$$

The fitted residuals, divided by 100, are considered to be the innovations in liquidity. Such a filtering process is necessary to remove the predictable component of liquidity factor changes, as well as the impact of lagged values of the scaling factor.

The second measure of market-wide liquidity used here is attributable to Brennan, Chordia and Subrahmanyam (1998). Dollar volume is argued to be positively correlated with market-wide liquidity. Hence, I use the dollar value of market-wide trading volume as one of my liquidity measures. Dollar volume is defined here, quite simply as the number of shares traded during the month, multiplied by the price per share at the end of the month. At this point, a cross-sectional value-weighted average is taken to represent aggregate liquidity:

$$\left(\frac{1}{N_t}\right)\sum_{i=1}^{N_t} P_t^i V_t^i, \quad (14)$$

where P_t^i is the price per share at the end of the current month, V_t^i is the number of shares traded for security i during month t . This is a simple metric, and the cross-sectional average is used here as a measure of market wide liquidity.

The third measure used here is attributed to Stoll and Whaley (1983), Amihud and Mendelson (1986) and others. Bid/ask spreads have long been considered a measure of market liquidity, since the spread represents the price charged by the market maker for providing liquidity to the trader. If market liquidity is low, the spread tends to increase. Here, daily bid/ask spreads are aggregated and used as a measure of market liquidity.

For all stocks with available data, the month t average end-of-day bid/ask spread is calculated. At which point, a cross-sectional average is taken of all stocks with spread data available. The measure is calculated as follows:

$$-\left(\frac{1}{N_t}\right)\left(\frac{1}{t}\right)\sum_{i=1}^{N_t}\sum_{j=1}^t S_{ij}, \quad (15)$$

where S_{ij} is the bid/ask spread for the firm i on day j of the given month, with the average taken across all stocks. This measure captures aggregate liquidity in the form of bid/ask spreads, which are decreasing in market liquidity. The negative sign is included to make the results easily interpretable (since for all measures used, higher values imply more liquid markets).

A fourth confirming measure of market liquidity is a variant of that which is used by Amihud (2002). Given that liquidity for an individual stock can be measured by contemporaneous price impact, one can simply measure individual stock liquidity as follows:

$$ILLIQ_{i,t} = \frac{-1}{DN} \sum_{k=1}^D \sum_{i=1}^N \frac{|r_{i,t}|}{VolD_{i,t}}, \quad (16)$$

where D is the number of trading days during the given month, $VolD_{it}$ is the total number of shares traded for stock i on day t . The monthly panel average is taken over all securities and all trading days during the given month. Each month, these measures are created, forming a monthly measure of aggregate market liquidity. This measure relies on contemporaneous price impact of trade to capture the essence of liquidity changes in the market. A sufficiently shallow market is one in which the price impact of trade is abnormally high. Again, the negative sign in front of this measure is included to help with the interpretability of results.

III. Style Analysis results

A. The sample

All funds used here are those classified as either asset allocation or balanced funds according to the Morningstar Principia Pro Mutual Fund CD. The time period covered is January 1, 1997 through December 31, 2002. This time period was chosen due to the availability of daily bond index returns. All funds which report to have greater than 10% of their assets invested either internationally or not in one of the 3 major asset classes (stocks, bonds or cash) is removed from the sample.

All funds with significant restrictions on their investment activity are also not included into the sample. These may include funds that are restricted to social awareness activities, non-diversified funds, funds of funds, and funds with a fixed horizon or targeted maturity. Also, those funds which engage in strategies leading to non-linear payoff mappings through the use of deriva-

tives are not included. If the fund explicitly states that it uses derivatives, it is excluded, or if the empirical methodology rejects the presence of a meaningful linear relationship between fund returns and index returns, the fund is excluded. Only 4 funds are excluded according to the latter criterion.

All funds used here must be available at the beginning of the sample period. Survivorship bias is not an issue, since funds are included until they are either de-listed, acquired or change investment objective.

Here I calculate the daily return series for each fund in the following way:

$$r_{pt} = \frac{nav_{pt} + div_{pt}}{nav_{p,t-1}} - 1, \quad (17)$$

where

nav_{pt} = net asset value of fund p at the end of day t ;

div_{pt} = dividends of fund p on day t .

Bloomberg is used to hand collect daily net asset values, dividend information and fund distributions of any kind. All questionable data points are verified with Yahoo Finance or the Wall Street Journal. Any questionable distribution dates are verified by using either Standard and Poor's Annual Dividend Record or Moody's Dividend Record.

All hedge funds are excluded because a) these funds do not tend to have regularly available public information, and b) they are allowed to use non-linear trading strategies, or strategies involving very little diversification. The empirical techniques used here assume that the funds are well-diversified, since estimation of class holdings is easier when the fund's return has a relatively large systematic component.

Table 1

The mutual fund sample

| | |
|---|--------|
| Number of funds | 149 |
| Annual return, 1997-2002 | 5.7% |
| Annual return in excess of S&P 500, 1997-1999 | -13.1% |
| Annual return in excess of S&P 500, 2000-2002 | 10.2% |
| Range of stock allocations | 15.6% |
| Range of bond allocations | 18.6% |
| Range of cash allocations | 12.0% |
| Annual portfolio turnover | 86.9% |
| Annual expense ratio | 1.06% |

From January 1997 through December 2002, a sample of hybrid mutual funds were collected. The average returns in excess of the S&P 500 were calculated, along with share turnover, expense ratios and the range of stock and bond allocations.

Table 1 presents general fund statistics. 149 funds remain after all restrictions have been imposed. The fund sample is identical to that which is used in Comer, Larrimore and Rodriguez (2004). It is clear that the funds engage in a wide range of trading strategies. Stock, bond and cash allocations have ranges of 15.6%, 18.6% and 12%, respectively. This implies that there is significant cross-sectional variation in fund holdings across the major asset classes. Annual returns for these funds are significantly higher during the 2000-2002 period than during the 1997-1999 period (10.2% vs. 13.1% – returns in excess of the S&P 500). The data shows that hybrid funds tended to have strong performance under weak market conditions. However, this abnormal performance is primarily driven by the fact that these funds have more flexible investment options

than other fund managers. During a period in which the S&P 500 has a strongly negative return, even those who did not participate in the market at all have positive returns relative to this index!

Table 2

Style analysis results

| 3 – INDEX MODEL | | 10 – INDEX MODEL | |
|-----------------|--------|----------------------------|--------|
| INDEX | WEIGHT | INDEX | WEIGHT |
| STOCKS | 54.28% | S&P 500 | 37.70% |
| BONDS | 39.95% | SMALL STOCK | 4.80% |
| CASH | 5.77% | GROWTH STOCK | 6.70% |
| | | VALUE STOCK | 17.50% |
| RSQUARE | 0.8137 | LONG MATURITY BOND | 2.40% |
| | | SHORT MATURITY BOND | 16.80% |
| | | HIGH QUALITY BOND | 0.90% |
| | | LOW QUALITY BOND | 5.60% |
| | | MORTGAGE BACKED SECURITIES | 5.30% |
| | | CASH | 2.40% |
| | | | |
| | | RSQUARE | 0.809 |

Hybrid fund weights are calculated by using a 3 and a 10-index model. The 3-index model includes the value-weighted returns from all stocks, all bonds, and cash portfolios. The 10-index model includes the value-weighted return to the S&P 500, the small, growth and value portfolios as calculated by Fama and French (1992), long and short maturity bond portfolios, high and low quality bond portfolios, mortgage backed securities, and returns on a cash index. The coefficients are estimated via constrained optimization, keeping all coefficients between 0 and 1 and presuming that all coefficients add to 1. For each fund/month, the daily returns of the fund are regressed on the various indices to produce the coefficient estimates. The data extend from January 1997 through December 2002.

Table 2 shows the results from 3 and 10 index style analysis. Daily return regressions are run for every firm/month in the sample. The table reports results from both the 3-index and 10-index models, including the average r-square from the regressions¹. The 3-index model coefficients show that the typical fund in my sample holds about half of its portfolio in stocks. This average is lower than that of the 10-index model, which argues that roughly 2/3 of the average fund's holdings are in stocks. I attribute this differentially primarily to a multicollinearity problem among the variables in the 10-index model. For example, the S&P 500 has correlations of .922, .835 and .793 with the returns on growth, value and small stocks, respectively. While the imperfect correlation serves to accentuate the ability of these indices to span the investment opportunity set, the regression model suffers in its ability to distinguish the contribution of one index over the other, particularly over a 21-day estimation period. It is for that reason that the 3-index model is going to be the focus of the paper, with the 10-index model only serving as a supplement. The multicollinearity issue goes away with the 3-index model, and the coefficients can be estimated more precisely. The loss of detailed manager holdings offered by the 10-index model is of only secondary importance in the questions being asked by this research.

A second differential between the two models is the percentage of cash and bond holdings. The 3-index model argues that roughly 40% of all holdings are in bonds, and the remaining 5.77% are in cash. These results are quite similar to those of Comer (2002). Fund managers tend to hold most of their portfolio in stocks. However, I am not concerned here with the differential between bond and cash holdings, since the analysis is focused on how fund managers react to

¹ Statistically speaking, the r-square is only constrained to be between 0 and 1 if there is a constant in the sample. However, there is no theoretical justification for the inclusion of a constant in the regression model used here. The r-squares here should be interpreted in the same manner as those of Sharpe (1992).

changes in equity market liquidity. Therefore, the questions being asked are simply stated so as to be able to extract meaningful, precise inferences that are devoid of the problems that come with attempting to detect subtle differences presented by coefficients that are noisy by definition. The only way to truly know what fund managers are doing at all times is to have access to fund manager holdings. To date, this has not been possible.

Description of liquidity measures

The 4 liquidity measures are calculated by using the entire time series of data, spanning from January, 1997 through December, 2002. For simplicity, I refer to the dollar volume measure as the “Brennan” measure, the residualized liquidity measure as the “Pastor Stambaugh (P-S)” measure, the price-impact based measure as the “Amihud” measure, and the spread-based measure as the “Spread” measure. Of course, this is not to imply that these authors are the ones solely responsible for the derivation of these measures. A great deal of credit is attributed to all authors who contributed to the understanding of liquidity.

Table 3 presents the descriptive statistics for all of the liquidity-based measures. The mean, standard deviation, 10th and 90th percentiles are presented for all liquidity measures used here. The averages are taken during the 1997-1999 period (the bear market) and the 1999-2002 period (bull market). The first thing to notice is that during the recent bull market, equity markets have indeed become more liquid. Three out of four measures show that market liquidity has improved during the bull market from 1999 through 2002. The P-S measure shows the most dramatic increase, as the mean liquidity shock during the bear market is negative, while during the bull market it is positive. The fact that the P-S measures have been carefully orthogonalized with respect to market returns argues that these liquidity effects are indeed distinct from movements in share prices themselves. All measures except for the Amihud measure have become more volatile as well.

The various measures of market liquidity are all positively correlated, but not perfectly so. This is due to the manner by which each model defines liquidity. The P-S model, for example, relies on price reversals to define periods of low liquidity. The Brennan model simply relies on the magnitude of dollar volume. While agreement among these 4 measures does not prove a relationship with certainty, from a statistical standpoint, it certainly increases the likelihood that a relationship exists.

IV. Liquidity tests

Table 4 shows the changes in fund manager holdings before, during and after low liquidity months. Here, a liquidity shock is defined as a month in which the equity market liquidity is one standard deviation below the mean. Market liquidity is defined according to the 4 measures mentioned above. Additionally stated are the fund attribution returns before, during and after low liquidity months. The most striking result is that the typical hybrid fund manager shows the ability to move out of stocks *before* months in which market liquidity is going to be dramatically lower. Using all 4 measures of liquidity, it is shown that fund managers shift out of stocks and into bonds the month before major liquidity shocks. This argues in favor of the ability of hybrid fund managers to time changes in equity market transactions costs.

The measures are all in relative agreement regarding the magnitude of the holdings changes that take place. The smallest change is -3.02%, given by the P-S model, and the largest is -6.00%, given by the Jones model. Therefore, the models are not only in agreement in sign and statistical significance, but they are also in relatively strong agreement in economic significance as well.

Table 3

Liquidity measures

| | MEAN | | | | | STANDARD DEVIATION | | | | |
|-----------------------------------|-------|------------------|---------|---------|--------|--------------------|--------|--------|--------|--|
| | N | BRENNAN | P-S | AMIHUD | SPREAD | BRENNAN | P-S | AMIHUD | SPREAD | |
| 1997-1999 | 5731 | \$ 43,976,565.27 | -3.72% | -12.454 | 5.67% | \$ 21,679,885.91 | 43.62% | 4.80 | 0.78% | |
| 1999-2002 | 4656 | \$ 78,190,479.51 | 3.79% | -11.95 | 5.76% | \$ 26,389,124.93 | 54.69% | 2.33 | 1.34% | |
| OVERALL | 10387 | \$ 59,949,691.18 | -0.32% | -12.228 | 5.71% | \$ 29,445,412.92 | 49.09% | 3.90 | 1.08% | |
| 10TH PERCENTILE | | | | | | | | | | |
| | | BRENNAN | P-S | AMIHUD | SPREAD | BRENNAN | P-S | AMIHUD | SPREAD | |
| 1997-1999 | | \$ 22,829,142.39 | -64.33% | -16.491 | 4.79% | \$ 79,111,910.31 | 43.45% | -9.36 | 6.61% | |
| 1999-2002 | | \$ 50,942,403.63 | -51.72% | -15.365 | 4.60% | \$ 112,312,153.19 | 44.10% | -9.58 | 6.72% | |
| OVERALL | | \$ 24,658,088.16 | -63.23% | -15.754 | 4.77% | \$ 100,643,064.71 | 43.45% | -9.45 | 6.65% | |
| 90TH PERCENTILE | | | | | | | | | | |
| | | VARIABLE | BRENNAN | P-S | AMIHUD | SPREAD | | | | |
| | | BRENNAN | 1.00 | 0.04 | 0.27 | 0.17 | | | | |
| | | P-S | 0.04 | 1.00 | 0.01 | 0.11 | | | | |
| | | AMIHUD | 0.27 | 0.01 | 1.00 | 0.81 | | | | |
| | | SPREAD | 0.17 | 0.11 | 0.81 | 1.00 | | | | |

Descriptive statistics are presented for all liquidity measures used in this paper. "Brennan" refers to the dollar volume of shares traded, multiplying end of month share price by the total number of shares traded. P-S refers to the measures used in Pastor and Stambaugh (2003), Amihud refers to the negative of the cross-sectional average of the liquidity measures used by Amihud (2002), and Spread is the cross-sectional average bid/ask spread.

Table 4

Shifts between asset classes

| | | PASTOR-STAMBAUGH | | | BRENNAN | | |
|-------|----------|------------------|--------|--------|---------|--------|--------|
| | | AFTER | DURING | BEFORE | AFTER | DURING | BEFORE |
| PARMS | CR | -2.37% | -1.97% | -3.02% | -1.79% | -3.34% | -4.99% |
| T | CR | -6.04 | -4.29 | -6.60 | -3.42 | -6.20 | -9.27 |
| PARMS | GP | -1.16% | 3.72% | 3.89% | -2.32% | 1.24% | 0.68% |
| T | GP | -5.28 | 16.99 | 17.76 | -9.16 | 4.75 | 2.60 |
| PARMS | TB | 3.89% | -1.75% | 0.49% | 4.11% | 2.10% | 4.31% |
| T | TB | 8.50 | -3.77 | 3.96 | 7.76 | 3.84 | 7.87 |
| PARMS | 10 INDEX | 1.56% | -1.14% | 0.25% | -0.40% | -2.85% | 1.03% |
| T | 10 INDEX | 12.69 | -9.14 | 2.19 | -2.82 | -19.79 | 7.06 |
| PARMS | 3 INDEX | 1.39% | -1.25% | -0.86% | 0.37% | -2.82% | 1.31% |
| T | 3 INDEX | 12.14 | -10.83 | -1.85 | 2.74 | -21.14 | 9.65 |
| | | SPREAD | | | AMIHUD | | |
| | | AFTER | DURING | BEFORE | AFTER | DURING | BEFORE |
| PARMS | CR | -5.41% | -6.47% | -6.00% | -2.63% | -4.26% | -5.82% |
| T | CR | -11.48 | -13.76 | -12.74 | -5.37 | -8.73 | -11.98 |
| PARMS | GP | -0.27% | -0.90% | 4.71% | -0.28% | 0.59% | 3.27% |
| T | GP | -1.16 | -3.92 | 20.87 | -1.16 | 2.49 | 13.87 |
| PARMS | TB | -0.29% | -1.07% | -1.81% | -0.68% | -1.34% | -2.04% |
| T | TB | -2.23 | -8.23 | -14.12 | -5.04 | -10.07 | -15.42 |
| PARMS | 10 INDEX | 0.20% | -0.65% | -2.09% | -0.66% | -1.05% | -2.30% |
| T | 10 INDEX | 1.62 | -5.38 | -17.60 | -5.32 | -8.49 | -18.83 |
| PARMS | 3 INDEX | 5.68% | 7.37% | 1.29% | 2.91% | 3.67% | 2.56% |
| T | 3 INDEX | 11.88 | 15.51 | 2.68 | 5.86 | 7.40 | 5.15 |

Style analysis is performed for all funds presented in this paper. The 3-index model coefficient weights are regressed on dummy variables taking the value of 1 if the market-wide liquidity measure is one standard deviation below the mean and 0 if it is not. Also, the attribution returns from the 10 and 3-index models are regressed on the dummy variables as well. CR, GP and TB represent the changes in holdings for stocks, bonds and cash, respectively. 10 INDEX and 3 INDEX are the attribution returns for the 3 and 10 index models, respectively. Pastor-Stambaugh, Brennan, Amihud and Spread are the 4 liquidity measures described above.

The second key result is that all models argue that fund managers shift out of stocks *during* negative liquidity months. This is not the result of timing ability, but perhaps a reflection of the fund manager's desire to remove funds away from equity markets during months in which the cost of trading is very high. This result does not have a clear interpretation, since it is presumed to be equally costly to sell stocks as it is to buy them during these periods. Also, the sales may be driven by fund redemptions that take place during periods of low market liquidity. To the extent that equity market liquidity crises are correlated with macroeconomic liquidity shocks, one can argue that fund redemptions may increase due to liquidity shocks experienced by the investor (i.e. the need to convert shares to cash for some non-equity market related purpose). At any rate, the model shows that the proportion of fund assets invested in equity markets tends to decline during months of low market liquidity.

During the month following aggregate liquidity shocks, all models agree that funds are again removed from equity markets. This appears to represent some form of positive feedback trading resulting from the increased transaction costs that have occurred the prior month. Again,

the model ranges are very tight, from -2.63% for the Amihud model, to -5.41% from the Jones model.

The focus here is not on whether or not the fund managers shift from stocks to bonds or cash. Also, the models are not in strong disagreement in this regard. But generally speaking, there is a consensus among the models that bond holdings tend to increase *before* low liquidity months. The range of increases in bond holdings before low liquidity months is a bit broader than those for cash, although 3 out of the 4 models are within 1% of one another. There appears to be evidence that hybrid fund managers exhibit a flight toward liquidity the month before sharp reductions in equity market liquidity. The shift from stock markets to bond markets before such periods may serve as evidence of timing ability.

Attribution returns in response to reactions to market-wide liquidity shocks

I do not expect the seemingly-wise decision of the average hybrid fund manager to shift out of stocks right before periods of low liquidity to necessarily reveal itself in the magnitude of attribution returns. This reflects the fundamental weakness of the attribution return methodology. While attribution returns have the benefit of being normally distributed, time-varying and fund-specific benchmarks. They have the disadvantage of not adjusting for major risk shifts of the fund manager. For example, an efficient market implies that risk and return should be positively correlated. Therefore, on average a shift toward stocks is going to lead to a higher return than a shift toward bonds. An insightful fund manager may recognize this fact, but he/she may also recognize the fact that the Sharpe Ratio for stocks has declined dramatically, while that for bonds may have increased. So, while the magnitude of the return is going to be lower for bonds than stocks, the efficiency of the investment is greater for bonds than stocks during these periods. At the same time, this fund manager is going to appear to have a negative attribution return, since the passive weights are measured by using holdings from the previous month.

I circumvent this problem later in the paper by decomposing attribution returns in order to more accurately account for risk changes. While I do not know of an asset-pricing framework that is perfect, I do think that this set up presents a marked improvement over using raw attribution returns.

There is not much to be obtained from attribution returns during the month before major changes in market-wide liquidity. The key questions are whether or not these fund managers have the ability to add value for investors during low liquidity months. The returns earned before and after low liquidity months are not studied. According to the 10-index model, the average attribution return is negative during low liquidity months. All 4 models agree on this statement. The negative attribution returns are likely a result of the fact that the average return for bonds tends to be lower than that for stocks. Therefore, using raw attribution returns in this context will lead to the misperception that the average fund manager is not adding value for the investor. This is likely an incorrect perception, since it has been shown that these managers tend to leave stocks before, during and after months of low liquidity. Our decomposition in the following section will give a more precise indication of the extent to which fund manager behaviors add or destroy value for investors during these periods.

Attribution return decomposition

As mentioned earlier, the problem with raw attribution returns is that they are not reflective of the true value of fund manager decisions. An investor can choose to invest in an asset class that has a much lower return, but this is not necessarily a bad investment, given that returns without risk adjustments are meaningless. The use of a set of factor loadings from the previous month is meaningless if the manager has significantly altered his/her style holdings the following month.

I work to overcome this problem by decomposing attribution returns as follows:

$$r_{it} = \alpha + \beta_1 C_{it} + \beta_2 \Delta_{it} + \varepsilon_{it}, \quad (18)$$

where

$$\begin{aligned}\beta_1 &= \gamma_1 + \delta_1 N_t \\ \beta_2 &= \gamma_2 + \delta_2 N_t\end{aligned}\quad (19)$$

where N is a dummy variable taking the value of 1 when the level of market liquidity is more than one standard deviation below the mean. C is the fund's estimated percentage holding in stocks from the previous month, and Δ_{it} is the change in stock holding from month $t-1$ to month t . The coefficients are further conditionalized on the level of market-wide liquidity during that month.

Table 5

Attribution return decomposition

| | | PASTOR-STAMBAUGH | | BRENNAN | |
|-------|----------|------------------|----------|---------|----------|
| | | CRNEG | DEVCRNEG | CRNEG | DEVCRNEG |
| PARMS | 10 index | 2.94% | -4.60% | -5.35% | -5.64% |
| T | T-stat | 5.03 | -3.98 | -20.14 | -3.34 |
| PARMS | 3 index | 2.36% | -4.58% | -5.20% | -7.06% |
| T | T-stat | 4.34 | -4.26 | -21.12 | -4.50 |
| | | SPREAD | | AMIHUD | |
| | | CRNEG | DEVCRNEG | CRNEG | DEVCRNEG |
| PARMS | 10 index | -2.16% | -4.46% | -2.30% | -9.55% |
| T | T-stat | -8.97 | -2.92 | -9.34 | -5.97 |
| PARMS | 3 index | -1.60% | -4.23% | -1.94% | -9.30% |
| T | T-stat | -7.12 | -2.97 | -8.44 | -6.25 |

The attribution returns for the 3 and 10-index models are decomposed as follows: $r_{it} = \alpha + \beta_1 C_{it} + \beta_2 \Delta_{it} + \varepsilon_{it}$, where $\beta_1 = \gamma_1 + \delta_1 N_t$ and $\beta_2 = \gamma_2 + \delta_2 N_t$. The regressions are run in a panel framework, across all funds in the sample, and using dummy variables that take the value of 1 during low liquidity months and 0 otherwise. The interpretation of the coefficients goes as follows: DEVCRNEG is the average marginal impact on the attribution return for firms with high shifts into stocks during low liquidity months. CRNEG is the average marginal impact on attribution return for firms with high holdings in stocks during low liquidity months.

The regression is estimated in a panel framework, with all funds in the sample. All 4 liquidity models agree that when fund managers shift more heavily toward stocks during low liquidity months, their attribution returns are going to be lower than otherwise. 3 out of 4 models have coefficient magnitudes that are within 1% of one another, and all are of the same sign. This is in contrast to the fact that a shift toward stocks typically leads to a higher return than a shift toward bonds.

Secondly, 3 out of 4 models agree that high holdings in stocks lead to lower attribution returns during low liquidity months. This confirms the fact that it behooves the fund manager to shift out of this asset class before months that have low liquidity. Of course, a cross-sectional regression compares attribution returns of a given fund to the cross-sectional and time average attribution returns for all funds in the sample, so the regression is stating that funds which have higher holdings in stocks during low liquidity months tend to perform worse relative to their own time-varying benchmark than those funds which have smaller stock holdings. This is intuitive.

V. Robustness checks

An obvious question about these results is whether or not there is some correlation between equity market returns and liquidity measures that could be driving the relationship between

market-wide liquidity and movement out of stocks. Should it be the case that these liquidity measures tend to have low values at the same time that the market performs poorly, a reduction in stock holdings could simply be the result of a lower value in equity markets. For example, it is standard knowledge that when the value of an asset goes down, its percentage in the portfolio is going to decrease as well. If there is no rebalancing, then the percentage will be lower during the following month.

I check this potential problem by analyzing the correlations between equity markets and my liquidity measures during the period over which this sample is studied. If the correlations are too high, then reductions in stock values could be driving one of the key results, that fund managers tend to leave stocks during and after the months in which there was a liquidity shock. However, there is no reason to believe that such a correlation could drive the predictive ability of fund managers documented here.

Table 6

Correlation between stocks and liquidity measures

| | BRENNAN | P-S | SPREAD | AMIHUD | STOCKS |
|---------|---------|-------|--------|--------|--------|
| BRENNAN | 1.00 | 0.09 | 0.11 | 0.30 | -0.02 |
| P-S | 0.09 | 1.00 | 0.04 | 0.03 | -0.02 |
| SPREAD | 0.11 | 0.04 | 1.00 | 0.59 | 0.01 |
| AMIHUD | 0.30 | 0.03 | 0.59 | 1.00 | 0.02 |
| STOCKS | -0.02 | -0.02 | 0.01 | 0.02 | 1.00 |

This table presents the historical correlation between liquidity measures used here (described above). STOCKS represents the equal-weighted average return for all CRSP securities. BRENNAN, P-S, SPREAD, and AMIHUD are the liquidity measures.

The correlation matrix for the 1997-2002 time period is presented in Table 6. As the table shows, all of the measures have very small Pearson correlations with monthly returns in equity markets. The strongest correlation is -.02. So, while correlations with the equity market are certainly present, they are economically insignificant and do not appear to drive the results.

VI. Conclusion

I use a unique dataset to study the behavior of hybrid fund managers in response to major changes in equity market liquidity. Using this dataset, we are able to obtain insights into whether managers trade in reaction to major market liquidity changes, the degree of cross-sectional variation in response to these changes, and how managers react before, during and after major changes in market liquidity.

I document a flight to liquidity for hybrid fund managers. Also, hybrid fund managers who are able to time liquidity changes in equity markets are shown to add value for their investors. The results hold using various style index models, and also when using 4 measures of equity market liquidity.

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