Do Hedge Fund Managers Possess Timing and Selectivity Skill?

Evidence from Stock Holdings

by

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A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved April 10, 2013 by the
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ARIZONA STATE UNIVERSITY

May 2013

ABSTRACT

I study the performance of hedge fund managers, using quarterly stock holdings from 1995 to 2010. I use the holdings-based measure built on Ferson and Mo (2012) to decompose a manager's overall performance into stock selection and three components of timing ability: market return, volatility, and liquidity. At the aggregate level, I find that hedge fund managers have stock picking skills but no timing skills, and overall I do not find strong evidence to support their superiority. I show that the lack of abilities is driven by the large fluctuations of timing performance with market conditions. I find that conditioning information, equity capital constraints, and priority in stocks to liquidate can partly explain the weak evidence. At the individual fund level, bootstrap analysis results suggest that even top managers' abilities cannot be separated from luck. Also, I find that hedge fund managers exhibit short-horizon persistence in selectivity skill.

ACKNOWLEDGMENTS

I thank George O. Aragon, Michael G. Hertzel, Oliver Boguth, Esben Hedegaard, Yakov Amihud, Wayne Ferson, John Griffin, Haitao Mo, Laura Linsey, Illona Babenko, Yuri Tserlukevich, Claudia Costodio, Andra Ghent, seminar participants at ASU brownbag seminar and FMA doctoral consortium.

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Chapter 1

INTRODUCTION

Hedge fund managers are often perceived as savvy investment managers who can exploit their capacity for stock picking and market timing abilities without much limitation in their trading strategies. To profit from these opportunities, the smartest money managers have migrated to the hedge fund industry, thereby contributing to its dramatic growth in the last two decades.[1] A large literature has developed contemporaneously to examine whether hedge fund managers truly exhibit superior ability. An important theme in this literature is the difficulty of using the available fund returns data to measure performance, due to several potential measurement biases, including self-selection, and distortions between reported and economic returns (e.g., Bollen and Pool (2009), Fung and Hsieh (2000, 2001), Getmansky, Lo, and Makarov (2004), Jiang, Yao and Yu (2007), and Liang (2000, 2003)). In response to these challenges, a more recent strand of literature studies hedge fund managers' mandatory disclosures of quarterly portfolio holdings contained in Form 13F filings.[2] This approach can potentially sidestep many of the pitfalls associated with returns-based performance measures and utilize an array of weight-based measures applied extensively in other settings, like mutual funds.

I study hedge fund managers' performance using a large sample of quarterly holdings from 1995 to 2010. In particular, I build on Ferson and Mo (2012), who use a stochastic discount factor (SDF) approach that decomposes a manager's overall

[1] According to Griffin and Xu (2009), hedge fund assets under management (AUM) have increased roughly from $38 billion in 1990 to $2.48 trillion in mid-2007.
[2] According to Section 13(f) of the Securities Exchange Act of 1934, hedge funds with over $100 million under management are required to fill out 13F forms on a quarterly basis for all U.S. equity positions worth over $200,000, or more than 100,000 shares.

performance into several components: security selection, market return timing, and market volatility timing. The three components can be expressed as a covariance between a manager's portfolio weights and idiosyncratic stock returns (stock selection), market returns (return timing), and negative market volatility (volatility timing).

I extend the Ferson and Mo (2012) decomposition to address a third component of timing – *liquidity timing* – that measures the covariance between a manager's portfolio weights and market liquidity. To examine liquidity timing ability I construct a market-wide traded liquidity risk factor based on Amihud (2002). This will be discussed more in detail later.

At the aggregate level, I find that the average hedge fund manager delivers overall alpha of 2.08% (t-statistic 0.45), which represents selectivity alpha of 2.41% (2.54) per year and timing alpha of -0.32% (-0.07) per year.[3] [4] Although my point estimate can be economically meaningful as it covers the standard fixed management fees of 1 to 2%, the evidence is weak considering the conventional view of hedge fund managers' superiority and the high incentive fees of 15 to 20%. Griffin and Xu (2009) also provide weak evidence on hedge fund managers' abilities. They study hedge fund managers' stock holdings using Daniel, Grinblatt, Titman, and Wermer's (DGTW, 1997) characteristic-based performance measure, and conclude that hedge fund managers do not possess superior ability. However, I also explore other dimensions of abilities such as volatility

[3] For the definition of the "average fund," see panel A of Table 4.
[4] If I look at only "Long/Short Equity Hedge Strategy" (42% of the managers in my sample), the overall alpha is -27.22% per year (t-statistic -0.25), which represents selectivity alpha of 38.00% per year (2.52) and timing alpha of -65.22% (-0.61) per year. I determine a manager's investment style as the investment style which is most frequently used by its funds under management.

and liquidity timing, and more importantly, I shed additional light on why we do not find strong evidence to support the conventional view of hedge fund managers' superiority.

One possible explanation for the weak evidence is that the average hedge fund performance largely fluctuates over time; hence the time-series mean offsets all extremes and remains insignificant. To investigate this, I perform a year-by-year and structural breakpoint analysis, which reveals that the overall performance varies with market conditions. I find that the main determinant of the volatile performance is timing ability, which appears to be strongly pro-cyclical. In particular, during 2008 the total (timing) performance is –55.17% p.a. (–59.06% p.a.), whereas during 2009 it is 23.83% p.a. (16.69% p.a.). This observation of hedge fund managers' performance pro-cyclicality is in line with Patton (2008) who uses various different concepts of neutrality to present evidence against the market neutrality of hedge funds.[5] In a similar context, Jurek and Stafford (2012) develop a simple state-contingent framework for evaluating the cost of capital for hedge fund managers' non-linear risk exposures. They use the portfolio of writing index (S&P 500) put options and holding cash, and argue that the cost of capital estimated from the traditional linear factor model cannot cover the proper required rate of capital. Thus, the weak evidence of superior ability in this paper may suggest that a holdings-based measure can account for the hedge fund managers' non-linear risk exposure and impose proper cost of capital which is higher than that imposed by a

[5] If I look at only "Equity Market Neutral" managers (8.1% of the managers in my sample), the performance is far from being market neutral. The total alpha is -50.59% (-1.77) per month and 23.01% (1.10) per month during 2008 and 2008, respectively.

returns-based model.[6] That is, a stock-level linear factor model may be able to overcome the underestimation issue of cost of capital inherent in a portfolio-level linear factor model. In fact, with a holdings-based measure we can measure a fund's beta directly, and allow a fund' beta to change over time (on a monthly frequency in this paper), whereas with a returns-based measure we cannot measure a fund's exposure directly, and usually assume a constant beta over the entire sample period.

The change in the average fund's performance with market conditions may not be detectable with an unconditional model. Under the conditional model in which I incorporate market conditions into the performance measure, the timing component (0.17% p.a.) becomes positive, whereas the selectivity alpha (2.39% p.a.) remains similar to its level without conditioning information. Moreover, about 20% of the overall performance during 2008 can be accounted for by conditioning information. Thus factoring economic state in the performance measure can help avoid committing the mistakes of undervaluing managers' abilities.

The fluctuations of the average fund's performance with market conditions may also be explained by hedge funds' capital structure. It is theoretically well established that arbitrageurs' reliance on outside financing limits arbitrageurs' trading activities. (e.g., Shleifer and Vishney (1997), Vayanos (2004), Gromb and Vayanos (2002, 2010), Brunnermeier and Pedersen (2009)) That is, during crises, in response to the first sign of deteriorating performance, hedge fund investors and lenders will react promptly by redeeming their shares and issuing margin calls. To meet the surging redemption requests

[6] For the evidence of hedge fund managers' positive and statistically significant alpha based on a linear factor model and returns data, see e.g., Agarwal and Naik (2004), Fung and Hsieh (2004), and Hasanhodzic and Lo (2007).

and the heightened margin requirements, hedge funds may be forced to liquidate their positions at fire-sale prices. During market turmoil, the situation worsens because many other investors are also forced to sell off their positions at the same time. This behavior is detrimental to hedge funds' performance because it prevents fund managers from implementing discretionary trading due to the widened bid-ask spread and increased leverage ratio of funds. Thus, hedge funds that allow investors to withdraw their money on short notice or rely heavily on leverage may encounter more difficulty in exploiting their superior ability when the market is tight. I show that hedge funds with strong share restrictions outperform those with weak share restrictions by 6.23% (2.95) per year during 2008, and by 2.29% (2.90) per year over the sample period. The latter is consistent with Aragon (2007) who presents the evidence of liquidity premium embedded in the share restrictions in hedge fund industry. The debt capital constraints due to leverage do not seem to affect performance as much as share restrictions.

Also, given that the main determinant of the bad performance during market downturns is market return timing component, it is possible that facing forced liquidation hedge funds may prefer to sell off low market beta stocks, or that low market beta stocks happen to be those stocks subject to be liquidated first, like liquid stocks. This priority may expose hedge funds more to the market when the market return is low, causing their performance to deteriorate. This idea is similar to arguments in the previous literature which posits that there is a pecking order in stocks to sell off in the face of forced liquidation. (e.g., Ben-David, Franzoni and Moussai (2011), Brown, Carlin and Lobo (2010), and Scholes (2000) argue that investors put a higher priority on liquid stocks in the face of forced liquidation.) However, I find that they reduced their market return exposure during crisis both by selling high beta stocks and buying low beta stocks. Also, they spent more money in buying low market beta stocks than earned by selling high market beta stocks. But, the exposure was still positive, and the market excess return was way below its historical average, which yields negative market return timing ability. In addition, we observe that the market beta of the stocks purchased by the average fund was highest during the tech bubble.

In contrast, I find that the average hedge fund manager increased its exposure to the market liquidity during crisis by selling less sensitive stocks and buying more sensitive stocks. That is, they increased their exposure to the market liquidity when they were supposed to decrease. This implies their lack of liquidity timing ability. Indeed, I do not detect any significant results with respect to liquidity timing ability.

In addition, consistent with prior literature the average hedge fund appears to prefer to sell off liquid stocks during market downturns. So it seems that the average hedge fund manager liquidated liquid stocks with high sensitivity to market return and low sensitivity to market liquidity. In fact, the correlation coefficients among market beta, liquidity beta, and liquidity confirm these observations. Also, although I find that the correlation coefficient between liquidity and liquidity beta of the stocks held by hedge fund managers is overall negative over the sample period, it closes to zero during crisis. This may advocate Sadka and Lou (2011) who argue that stock-level liquidity and liquidity risk (beta) are different concepts by showing that liquid stocks underperformed illiquid stocks during the recent financial crisis and that the performance of stocks during the crisis can be better explained by historical liquidity beta than stock-level liquidity.

Another possible story for the pro-cyclical movement of the average fund performance is that 13F data does not provide complete picture of all holdings, so we cannot observe their other positions which can possibly deliver positive alpha. Using funds' returns data which reflect the performance from complete holdings, and 36-month rolling window, I find that the average fund exhibits positive market return timing, but negative liquidity- and volatility timing abilities during the recent financial crisis, but overall they do not appear to possess any timing abilities. In addition, the use of derivatives does not seem to be related to the time-variation of performance. Thus it is possible that during crisis, hedge funds attempted to time the market return during crisis using short positions, but it does not look like other positions are material in the average manager's performance.

Although I do not find much evidence supportive of superior ability at the aggregate level, it is possible that there are some managers in the extreme of the cross-section who exhibit significantly positive performance. However, to investigate top managers, we need to rank managers according to their alphas, and consider order statistics. So our statistical inference needs to rely on the joint distribution of over 600 managers' skill distributions. Moreover, hedge fund managers' abilities are likely to be non-normal, correlated with each other, and heterogeneous, which makes it more difficult to impose an ex-ante parametric distribution from which fund returns are assumed to be drawn. In this situation I follow previous studies and employ a bootstrap procedure which does not rely on an ex-ante parametric distribution but on an ex-post empirical joint distribution. (e.g., Kosowski et al. (2006), Kosowski, Naik, and Teo (2007), Jiang, Yao, and Yu (2007)). I find that even top managers do not exhibit skill which can be distinguishable from luck. This is in contrast with Kosowski, Naik, and Teo (2007), who study hedge fund performance using returns data and bootstrap and Bayesian approach, and conclude that top hedge fund performance cannot be explained by luck alone. This may suggest that the performance effect of market conditions outweighs that of randomness.

Furthermore, hedge funds exhibit a short-horizon performance persistence in selectivity skill, but not long-horizon persistence. This result may be in accordance with Berk and Green's (2004) model in which the combination of managers' differential ability, decreasing returns to scale, and investors' rational provision of capital to funds results in zero risk-adjusted, after-fee returns to the investors.[7] Also, considering the volatile movement of performance the lack of persistence in performance is not that surprising.

The main contribution of this paper is that (i) I provide several possible explanations for the weak evidence on hedge fund managers' superiority by exploring the time-variation and decomposition of hedge fund managers' performance, share restrictions, forced liquidation, and conditioning information, (ii) I introduce a liquidity timing ability under a holdings-based measure for the first time, and (iii) I conduct bootstrap analysis using holdings data to study the cross-section of hedge fund managers' various abilities for the first time.

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[7] Fung et al. (2008) provide empirical evidence in support of the rational model, using fund-of-funds returns data. Also, Griffin and Xu (2009) find a lack of performance persistence with the DGTW measure using hedge fund equity holdings data during 1992-2004. In contrast, Jagannathan, Malakhov, and Novikov (2010) find significant performance persistence among superior funds, but little evidence of persistence among inferior funds.

The remainder of the paper is organized as follows. Chapter 2 looks at the relevant literature. Chapter 3 discusses performance measure and estimation method. Chapter 4 describes the sample. Chapter 5 documents the results, and Chapter 6 concludes.

Chapter 2

LITERATURE

The current article is related to three strands of literature: (i) a holdings-based performance measure, (ii) hedge fund managers' ability, and (iii) performance decomposition.

This paper relies on a holdings-based performance measure to investigate hedge fund managers' ability. A number of empirical studies have provided a good amount of evidence that hedge fund returns data suffer from several measurement biases. Fung and Hsieh (2000) discuss a selection-, an instant history- , and survivorship bias. A selection bias occurs because only funds with good performance want to be included in a database and funds with poor performance can refuse to participate in a vendor's database. An instant history bias occurs when hedge funds come into database vendors with instant histories which usually exhibit good track records, and the database vendors backfill the hedge funds' performance. Lastly, survivorship bias occurs if funds drop out of a database because of poor performance and database vendors only contain information for those hedge funds that are still operating. Getmansky, Lo, and Makarov (2004) argue that the high serial correlation in hedge fund returns is likely the outcome of liquidity exposure and smoothed returns. If funds hold illiquid securities which are not actively traded and the market prices of which are not readily available, then the reported returns of these funds appear to be smoother than the economic returns which fully reflect all the available market information about the securities, which in turn will impart a downward bias on the estimated return variance. Furthermore, Bollen and Pool (2009) find a significant discontinuity in the distribution of monthly hedge fund returns at return of zero after controlling for database biases such as survivorship bias. By showing that this discontinuity disappears when using bi-monthly returns or three months' returns before an audit, they argue that hedge fund managers temporarily distort monthly returns to avoid reporting losses. Moreover, Liang (2000, 2003) finds significant differences in reported returns of the same funds between different databases.

To overcome such biases of hedge funds' reported returns, several recent empirical papers examine hedge fund performance using holdings data.[8] Griffin and Xu (2009) study hedge fund managers' performance using quarterly 13F holdings of hedge funds, and conclude that hedge funds exhibit no ability to time sectors or pick better stock styles and raise serious questions about the perceived superior skill of hedge fund

[8] The literature notes several weaknesses in employing holdings data instead of returns data: (i) First, we have to limit our investigation to long equity positions. According to Fung and Hsieh (2006), 43% of hedge funds in the TASS database (and 32% of AUM) were invested in long/short equity strategies as of 2004. Also, 81% of hedge funds (76% of AUM) in their investigation are categorized as equity-oriented funds, i.e., convertible arbitrage, emerging market, equity market neutral, event driven, global macro, and long/short equity. Further, Aragon and Martin (2011) manually collect 13F filings and document that filings in options are a small proportion of hedge fund equity positions, although this observation is based only on the set of 13F-reportable securities and exchange-traded derivatives, which is small compared to OTC derivatives. (ii) Also, we can observe holdings on a quarterly basis. But the average quarterly turnover rate for the sample in this study is 21.9%. As the definition of turnover, I use the minimum of total buys and total sales, divided by the mean of current and lagged total equity holdings. (Brunnermeier and Nagel (2004) and Ben-David, Franzoni, and Moussawi (2011) report the average quarterly turnover in their hedge fund sample as 25% and 39.4%, respectively.) This turnover rate legitimizes the use of a quarterly snapshot of holdings data to capture the low-frequency component of hedge fund trading. By splitting the sample into terciles according to the average quarterly turnover, and forming an equally weighted portfolio of going long the top turnover funds (average quarterly turnover of 37.0%) and short the bottom funds (7.0%), I find that the turnover matters only during the tech bubble (see Figure 7). However, I acknowledge that if hedge fund managers employ the strategies of buying and selling the same stocks within a quarter, we cannot capture such an activity. (iii) Furthermore, we can observe only large managers, which are subject to 13F filings requirements. We cannot observe the long equity positions of those hedge funds that are not subject to 13F filings. To address this issue, I examine the size effect within 13F hedge fund managers by splitting the sample into terciles and quintiles according to the AUM (I aggregate the time-series average AUM across funds under a management firm). I find no significant difference in performance between the top and bottom portfolios. (iv) Finally, the holdings information is at the management firm level, not at the fund level as in mutual funds. To address this issue, I split the manager sample into terciles depending on the number of funds under a manager. I find no significant difference in overall performance between the top portfolio (the average number of funds under a manager is 14.3) and the bottom (the average number of funds under a manager is 1.0, i.e., the manager level is the same as the fund level). However, the timing alpha of the top portfolio is 0.48% p.a. (t-statistic: 1.88) lower than that of the bottom.

managers. To measure performance they rely on characteristics-matched benchmarks (DGTW), which control for size, value, and momentum effects. Brunnermeir and Nagel (2004) focus on hedge funds' positions in tech stocks (high price-to-sale stocks) during the technology bubble from 1998 to 2000, and find that hedge funds were able to adjust their positions in tech stocks to capture the upturn and avoid the downturn. Using a unique dataset Aragon and Martin (2012) show that hedge fund managers' long equity option positions can predict the directional and non-directional movement of the underlying stocks. Agarwal et al. (2012), and Aragon, Hertzel and Shi (2012) investigate confidential positions in 13F filings and find evidence of hedge fund managers' capacity for informed trading.

Although portfolio managers' performance can be evaluated in various respects, the existing literature mostly focuses on a specific aspect of ability. Namely, they look at only one of the following: market return timing, market volatility timing, and stock-picking skill. The literature on timing measure stems from Treynor and Mazuy (1966) who look at the characteristic line of fund rate of return against the market return. If a manager can outguess the market, the manager will increase the portfolio sensitivity to the market (slope of the line) in anticipation of market rise and decrease in anticipation of market fall, so the characteristic line would exhibit a convex upward line. But they find that all but one of the mutual funds they investigated (57 funds) exhibit no curvature, so they conclude that managers cannot anticipate the major turns in the stock market. Henriksson and Merton (1981) investigate mutual fund managers' market timing ability based on the covariance between market beta and the indicator variable for the sign of excess market return, to measure managers' ability to forecast positive market excess return. This permits them to identify the separate contributions from stock picking and market timing skills, which are mixed in the Jensen's alpha from the linear regression. Busse (1999) studies mutual fund managers' ability to time market volatility considering that market volatility is persistent and so predictable and that performance measures are risk-adjusted. Using mutual funds' daily returns data he shows that funds that reduce systematic risk when market volatility is high earn higher risk-adjusted returns. Jiang, Yao, and Yu (2007) investigate mutual fund managers' market return timing ability using holdings data. They directly measure funds' market beta as the weighted average of the betas of the individual stocks held in the portfolio, and timing ability as the covariance between fund betas at the beginning of a holdings period and the holding period market returns. They find that mutual managers can time the market, which opposes to the previous evidence of insignificant or negative market timing ability of mutual funds based on returns data.

A couple of papers deal with various abilities using holdings data. Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) study mutual fund managers' holdings data and develop a characteristic-based performance measure. They construct benchmarks by matching stocks held by a manger to the 125 passive portfolios of similar characteristics such as market capitalization, book-to-market ratio, and prior performance. They find evidence supportive of characteristic selectivity but no evidence of characteristic timing. Ferson and Mo (2012) develop a holdings-based performance measures which accommodate market level timing, volatility timing, and stock selectivity skills based on a stochastic discount factor approach. They find no significant evidence of investment ability in mutual fund industry.

Also, some studies use returns data to investigate various abilities. Cao et al. (2012) use hedge fund returns and Treynor and Mazuy (1966) approach of CAPM regression to explore market liquidity timing ability at the individual fund level. They find that top managers can adjust their portfolios' market exposure to time market liquidity. But I do not find any evidence of liquidity timing ability in this paper. The main difference in results may be due to the fact that they assume a one-factor asset pricing model (CAPM), and measure liquidity timing ability as the covariance between market beta and liquidity risk (Pastor and Stambaugh's liquidity level factor), while I assume a two-factor model consisting of market return and market liquidity, and measure liquidity timing ability as the covariance between liquidity beta and liquidity risk.[9] Chen and Liang (2007) investigate hedge fund returns data to study the market timing ability of self-described market timing managers. They propose a market timing measure which jointly evaluates market return level- and volatility timing ability by regressing fund returns on the squared Sharpe ratio of the market portfolio. They find evidence of timing ability at both the aggregate and the fund level.

[9] If I use Pastor and Stambaugh (2002) traded liquidity risk factor, liquidity innovation, or liquidity level, I still do not have any significant results.

Chapter 3

PERFORMANC MEASURE AND ESTIMATION

In this section, I briefly discuss the performance measure used in this paper.[10] I assume a two-factor model consisting of market excess return and traded liquidity risk.[11] That is, the benchmark portfolio is

$$r_B^{'} = (r_M \; r_L),$$

where r_M and r_L represent market excess return and liquidity risk, respectively.

The asset pricing model basically says that the asset price is equal to the expected value of discounted asset payoff,

$$E(m_{t+1}x_{t+1}|\Omega_t) = p_t,$$

or in net return term,

$$E(m_{t+1}r_{t+1}|\Omega_t) = 0,$$

where m_t is a (inter-temporal) marginal rate of substitution, also called the stochastic discount factor (SDF) at time t, and p_t, x_t, r_t, and Ω_t are, respectively, asset price, an asset payoff, return in excess of risk-free rate at time t, and an information set available up to time t. In our setting the primitive assets are market excess return, liquidity risk portfolio return, and risk-free rate, so the pricing formula prices these assets.

[10] For details, see Cochrane (1996, 2005), Ferson and Lin (2012), Ferson and Mo (2012), and Ferson and Schadt (1996).

[11] If I use Carhart four factors along with traded Amihud liquidity risk or traded Pastor and Stambaugh (PS) liquidity risk factor, the magnitude of alpha is reduced but the overall pattern is similar. The results are available upon request. For simplicity, I develop the intuition based on a two-factor model.

Assuming a linear factor model is equivalent to representing SDF as a linear function of factors (Ross (1978), Dybvig and Ingersoll (1982), Cochrane (1996)). Therefore, assuming a two-factor pricing model, we have

$$m = a - b' r_B, \tag{1}$$

where r_B is our benchmark portfolio consisting of market return and liquidity risk portfolio return, and a and b are market-wide parameters.

Section 1

Unconditional Model

If a manager possesses superior information not included in the public-information set Ω_t, and can take advantage of it to realize superior portfolio returns, the model does not price the fund return. Then we can define an unconditional SDF-based abnormal performance measure as

$$\alpha_p = E\,(mr_p) - 0, \tag{2}$$

where m is the SDF and r_p is the return of the fund in excess of a short-term Treasury bill. By restricting to an unconditional measure - that is, only a constant term is in the information set - I assume any information can be proprietary.

Now consider a factor model regression for the excess returns of N underlying securities in a portfolio:

$$r = a + \beta' r_B + u, \qquad v = a + u, \tag{3}$$

where β is the $N \times 2$ matrix of betas, v the vector of abnormal or idiosyncratic returns, and $E(ur_B) = 0 = E(u)$.

If a fund forms a portfolio using weights x, then the portfolio return is given by

$$r_p = x'r = (x'\beta)r_B + x'v. \tag{4}$$

Note that $w := x'\beta$ is the weighted average of betas of individual stocks held by a fund, which represents the fund's beta to benchmark portfolio. Substituting equation (1) into the definition of alpha (2) we obtain

$$\begin{aligned}
\alpha_p &= a\,E(w'r_B) - b'E\big(r_B r_B' w\big) + E\,\{(a - b'\,r_B)x'v\} \quad (\because w = x'\beta) \\
&= a\,\{Cov(w_M, r_M) + Cov(w_L, r_L)\} - b'E\big\{\big[r_B r_B' - E\big(r_B r_B'\big)\big]w\big\} + E\{(a - b'\,r_B)x'v\} \\
&\quad (\because Cov\,(x, y) = Exy - ExEy;\ E\{(a - b'r_B)r_B\} = 0) \\
&= a\,Cov(w_M, r_M) + a\,Cov(w_L, r_L) - b'E\big\{\big[r_B r_B' - E\big(r_B r_B'\big)\big]w\big\} \\
&\quad + [aE(x'v) - b'E(r_B v'x)].
\end{aligned} \tag{5}$$

The first term in (5) captures market return level timing through the covariance between the portfolio weights set at the beginning of a period and the subsequent factor market returns. Similarly, the second term captures liquidity timing ability. The third term relates to volatility timing through the covariation between portfolio weights and the second moment matrix of benchmark returns, which is what Grinblatt and Titman (1989, 1993) missed.[12] The last term captures selectivity skill, which is the expected value of the interaction between portfolio weights and idiosyncratic abnormal returns, and excludes the part contributable to factors, which does not appear in traditional selectivity measures.

The market-wide parameters a and $b = (b_M\ b_L)$ are estimated based on the assumption that the benchmark portfolio and risk-free asset satisfy the pricing model, as shown in equations (6a) and (6b) below. For each fund, I estimate a market return timing

[12] They look at the covariance between portfolio weights and the returns of securities held in a portfolio, but view it in a little different way from the prior literature. They estimate a covariance as the expected value of security return multiplied by the deviation of portfolio weight from expected weight, and they proxy the expected weight as lagged weight. By doing so, they can address survivorship bias and the critique of the impact of a benchmark portfolio on performance measure.

component denoted as α_M, market liquidity risk timing ability α_L, a volatility timing component α_σ, and a selectivity component α_S. The model is estimated using the generalized method of moments (GMM, Hansen, 1982) through the following moment conditions:

$$\varepsilon_1 = (a - b'r_B)r_B \tag{6a}$$

$$\varepsilon_2 = (a - b'r_B)R_f - 1 \tag{6b}$$

$$\varepsilon_3 = r_B - \mu_B \tag{6c}$$

$$\varepsilon_{41} = \alpha_M - a\left(r_M - \mu_M\right)'w \tag{6d1}$$

$$\varepsilon_{42} = \alpha_L - a\left(r_L - \mu_L\right)'w \tag{6d2}$$

$$\varepsilon_5 = \alpha_\sigma + b'(r_B r_B')w - a\mu_B'w \tag{6e}$$

$$\varepsilon_6 = \alpha_S - [(a - b'r_B)v'x] \tag{6f}$$

$$E(\varepsilon) = E(\varepsilon_1,\ \varepsilon_2,\ \varepsilon_3,\ \varepsilon_{41},\ \varepsilon_{42},\ \varepsilon_5,\ \varepsilon_6) = 0. \tag{6g}$$

Stock betas for each risk factor and month are estimated using 60 monthly data prior to the current month, requiring at least 24 months of observations. For estimation I require each fund to have at least 15 observations, except for the yearly performance and persistence test, in which I require full 12 months of observations. I estimate the market-wide parameters using the first three equations, (6a) to (6c) subject to (6g), and then plugging the parameter estimates into to the other equations (6d1) to (6f) subject to (6g) to solve for alphas. I solve the system of equations for each fund using GMM with the Newey-West (1987) covariance matrix using three lags to account for autocorrelations and heteroskedasticity-consistent estimate of the standard error.

Section 2

Conditional Model

We can incorporate the effects of conditioning information into the model by either (i) scaling the returns (Hansen and Singleton (1982)), or (ii) scaling the factors (Ferson, Kandel, and Stambaugh (1987), Harvey (1989), and Shanken (1990)). In this paper, I use the latter.[13] In this case, the SDF can be represented by a linear combination of factors with weights as linear functions of instruments that change across different information sets; the conditional mean of factors can be expressed as a linear function of instruments. That is,

$$m_{t+1} = a' z_t - (b_M' z_t)\, r_{M,t+1} - (b_L' z_t)\, r_{L,t+1};$$

$$\mu_{M,t+1} = \mu_M' z_t,\ \mu_{L,t+1} = \mu_L' z_t,$$

where $r_{M,t}$ and $r_{L,t}$ are market excess return and liquidity risk factor at time t; $\mu_{M,t}$ and $\mu_{L,t}$ are conditional expectations of market excess return and liquidity risk factor at time t; a, b_L, b_M, μ_L, and μ_M are $L \times 1$ vectors of coefficients; and $z_t \in \Omega_t$ is a $L \times 1$ vector of instruments including a constant.

Now the moment condition (6g) changes so that it holds when we multiply both sides of the equation by any instrument. For example, if we have two instruments, we will have nine equations for parameter estimation and twelve equations for performance estimation.

Following the previous studies (Christopherson, Ferson, and Glassman (1998), Cochrane (1996), Ferson and Mo (2012), and Ferson and Shadt (1996)), I use a collection

[13] For details, see Cochrane (1996).

of public information variables that are shown to be useful for predicting security returns and risks over time: (i) the lagged three-month Treasury bill yield, (ii) the lagged dividend price ratio (iii) the lagged term spread, (iv) the lagged default return spread, and (v) a dummy variable for the month of January.

Chapter 4

DATA

The information on hedge fund returns, affiliations, and characteristics are from the TASS snapshot as of April 25, 2012. Because TASS has started to collect hedge fund data since 1994, it does not include defunct funds' performance information before 1994. Thus I choose the sample over the period January 1994 to December 2010 to control for the survivorship bias.

I obtain the 13F filers' names, their equity holdings and the holding stocks' prices data from the Thomson-Reuters Institutional (13F) Holdings database.

To identify 13F filers that manage hedge funds, I first create a list of non-duplicate hedge fund managers' names over the sample period, where hedge fund managers are defined as either a "management company" or an "investment company" in a company type field in the TASS database. Also, I make a list of non-duplicate 13F filers' names over the sample period. Then I manually match the hedge fund managers' names to the 13F filers' names.

To address the backfilling bias, I choose the observations after the date they were added to the TASS database. In the event that a hedge fund manager is matched to multiple hedge funds and hence to multiple dates added to TASS, I choose the earliest date added to TASS for the manager.

In terms of the predetermined information variables, (i) Treasury-bill rates are the 3-month Treasury bill, (ii) dividend price ratio is the ratio of 12-month moving sums of dividends paid on the S&P 500 index to the prices, (iii) the term spread is the difference between the long-term yield on government bonds and the Treasury bill, and (iv) the default yield spread is the difference between BAA and AAA-rated corporate bond yields.[14]

I retrieve individual stocks' information and Carhart four factors from the CRSP.[15] I expand the quarterly holdings data to the three months in the next month to compile monthly data.

In this paper I focus on a traded liquidity risk factor constructed from Amihud (2002) rather than Pastor and Stambaugh's (2003) traded liquidity risk factor. Goyenko, Holden, and Trzcinka (2009) investigate whether liquidity measures constructed from daily data can measure liquidity as well as those from intraday data. They find that Amihud (2002) measure is a good proxy for price impact, while Pastor and Stambaugh's (2003) gamma does not perform well compared to other measures. When we look at the cumulative traded liquidity risk factor over time (Figure 1), we can see little time-variations in the Pastor and Stambaugh's measure even during the crises like LTCM collapse, and tech bubble burst.[16] In contrast, we can observe a lot more variations in that of Amihud's liquidity measure. Thus, it seems that new measure based on Amihud (2002) is more appropriate to study whether or not hedge fund managers time market liquidity.

To construct a market-wide traded liquidity risk factor, I follow Amihud (2002) and Acharya and Pedersen (2005).[17] First I compute individual stocks' daily liquidity

[14] I thank Prof. Goyal for providing the data on his website: http://www.hec.unil.ch/agoyal/
[15] I thank Prof. Fama and Prof. French for sharing the data.
[16] Note that I discuss only "traded" factor to compute alpha. In terms of cumulative factor, their other factors (liquidity level and liquidity innovation) seem to exhibit enough time-variation compared to their traded factor. I thank Prof. Pastor and Prof. Stambaugh for sharing the data.
[17] I clean the daily stock return data in the following manner: (i) I use ordinary common shares (share code is less than 20), (ii) stocks listed on NYSE/AMEX (exchange code: 1, 2) (See Reinganum (1990) on the effects of the differences in microstructure between the NASDAQ and the NYSE on stock returns, after adjusting for size and risk. In addition, volume figures on the NASDAQ have a different meaning than those on the NYSE, because trading on the NASDAQ is done almost entirely through market makers,

measure as the negative signed ratio of absolute value of stock return to dollar volume. Then I compute the individual stocks' monthly liquidity measure as the average of daily liquidity measures. The market-wide monthly liquidity level measure is computed as the value-weighted average of individual stocks' monthly measures, where weight is determined by the prior month-end market capitalization. Then I obtain the monthly market-wide liquidity risk (innovation) as the residual of AR(2) process of the liquidity level using prior 60 months' observations. For each month, I sort stocks into deciles according to their liquidity betas which are computed using prior 60 months' observations requiring at least 24 months' observations and using a regression model of stock return on market return and market liquidity risk. Finally, I compute the traded market liquidity factor as the return to the spread portfolio by buying the most sensitive portfolio and selling the least sensitivity one. Here, portfolio return is computed as the value-weighted average of returns of the stocks in the portfolio where weight is determined by the prior month-end market capitalization.

The final sample contains (i) 13F filers managing hedge funds, (ii) their long equity holdings of the prior quarter-end, (iii) stock returns of the current month, (iv) stock betas for pricing factors, (v) pricing factors, and (vi) the previous month's instruments for each month.

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whereas on the NYSE most trading is done directly between buying and selling investors. This results in artificially higher volume figures on NASDAQ.), (iii) stocks whose number of price and volume observations within a month is at least 15, (iv) stocks whose prior month-end stock price is between $5 and $1,000 and prior month-end market capitalization exists. (v) stocks whose monthly liquidity measures lie between the 1st and below 99th percentiles. (vi) Also, volume is measured in $ million. Finally (vii) returns are adjusted for stock delisting to avoid survivorship bias. The last return used is either the last return available on CRSP, or the delisting return, if available. While a last return for the stock of -100% is naturally included in the study, a return of -30% is assigned if the deletion reason is coded in CRSP as 500 (reason unavailable), 520 (went to OTC), 551-573 (various reasons), 574 (bankruptcy), and 584 (does not meet exchange financial guidelines). (Shumway obtains that -30% is the average delisting return, examining the OTC returns of delisted stocks.)

Chapter 5

RESULTS

In panel A of Table 1, I document the summary statistics for pricing factors. In panel B, I report the estimates for the market-wide parameters using equations (6a) to (6c) subject to (6g). In panel C, I document the expected value of SDF, which is actually the inverse of the expected risk-free rate when we assume that the risk-free asset is a primitive asset in the pricing model.

Table 2 presents the summary statistics of the average fund's monthly exposure to each risk, that is, the weighted average of the market beta, liquidity beta, and idiosyncratic risk of individual stocks held by the manager, where weight is determined by holdings.

Panel A of Figure 2 depicts the average fund's monthly risk exposure over time. Market exposure appears to be slowly increasing over time with slight dips during the NASDAQ crash and the recent global crisis. The liquidity risk exposure has been increasing slowly since mid-2005 to hit the high in recent financial crisis. Also, the average fund slightly increased its liquidity exposure during the tech bubble burst. That is, the average manager seems to have been increasing its exposure to the market liquidity when they had to increase the most. Based on these observations, we can conjecture that managers may have market timing ability but no liquidity timing ability.

Table 3 reports the summary statistics of hedge fund industry in terms of size and holdings over the sample period. From panel A of Table 3 we can observe the increase in the number of hedge funds, and those subject to 13F, which reflects the growth of the industry over the past decade. Because the number of managers during 1994 ends up being only two in the final sample, I do not include this year in the analysis afterwards. Panel B documents the size of the equity holdings of hedge fund managers compared with CRSP total equity holdings.[18] To gauge the size of hedge funds subject to 13F, I examine the assets under management (AUM) in panel C, which shows that hedge funds subject to 13F are about two times bigger than their counterparts.

Table 4 documents the performance estimates of the average hedge fund manager. Panel A of Table 4 presents a simple example showing how I construct a single representative portfolio in the current paper. To form an equally weighted portfolio, for each quarter I take the average of the positions of the individual managers, with one over the number of managers of the quarter as an equal weight; to form a value-weighted portfolio, I take the average of the positions of the individual managers, with total equity holdings of the quarter as weights. I use an equally weighted portfolio so that large funds do not dominate the overall results. Unless otherwise stated, "average fund," "portfolio level," and "aggregate fund level" refer to an equally weighted portfolio. Panel B of Table 4 reports the performance estimates from equations (6d) to (6f), subject to (6a) to (6c) and (6g) for the average fund under unconditional model. The results show that the average fund exhibits total alpha of 2.08% per year (t-statistic 0.45), which represents

[18] As of 2010, the ratio of total equity holdings by hedge fund managers to CRSP total equity holdings (24.87%) seems to be larger than the findings of Griffin and Xu (2009) and Ben-David, Franzoni, and Moussai (2012), who document the figure as around 3% to 5%. This difference may be because they use a different sample period, proprietary data, or stricter filters than I do. For example, they use only those managers whose main line of operations is hedge fund business, they exclude large investment banks and prime brokers that might have internal hedge fund business, management companies for which the ratio of 13F AUM to TASS AUM exceeds 10%, and hedge funds with less than $1 million in total AUM, and they keep institutions of which more than half of their clients are classified as "High Net Worth Individuals" or "Pooled Investment Vehicles." In fact, the number of hedge fund management firms in Griffin and Xu (2009) and Ben-David, Franzoni, and Moussai (2012) are around 300 and 100, respectively. However, the medians are similar.

2.41% (2.54) of selectivity skill and –0.32% (–0.07) of timing ability.[19] Although it is statistically insignificant, the point estimate is economically meaningful as it can cover the standard fixed management fees of 1 to 2%. Also, note that the overall performance comes primarily from stock picking ability.

The weak evidence of the average fund's capacity for informed trading is somewhat surprising considering the conventional view of hedge fund managers' superiority and the high incentive fees investors are charged. One possible explanation for this weak evidence is that the average hedge fund performance is volatile over time, the time series mean of which fails to reflect such dynamics, thus producing insignificant estimates. To investigate the time-variation of performance, I look at a year-by-year performance. Yearly alpha is estimated using full 12 months' observations for each year, and the GMM estimation method (6d1) to (6f) subject to (6g). I use the same market-wide parameter estimates as before, that is, those reported in Panel B of Table 1. Indeed, we can observe that the yearly alpha of the average fund fluctuates over time, as presented in Figure 3.[20] Also, although 75% of the years deliver positive total alpha, negative alpha years are primarily identified as having historically large plunges in the magnitude of alpha. Moreover, the latter is usually matched to significant market events, such as the NASDAQ crash and recent financial turmoil, that is, –15.70% per year, –29.14% per year, and –55.17% per year correspond respectively to the 2001, 2002, and

[19] If I use the value-weighted portfolio, the magnitude of alpha is reduced but the overall pattern remains similar. The table is available upon request.

[20] Remember that the estimation method here is not like that for the usual regression of fund returns on multiple factors, in which we need to ensure the number of estimates does not exceed the number of observations. Rather, the alphas here are computed independently of one another; thus we do not need to worry about the degree of freedom to the extent that we do not care about the significance level.

2008. Therefore, the yearly performance is determined mainly by the timing component, which is in turn largely affected by market conditions.

To examine how performance changes with market conditions, I split the sample period into six sub-periods according to widely accepted structural break points: the period up to the collapse of Long-Term Capital Management L.P. (LTCM) and just before the tech bubble (January 1995 to September 1998), during the tech bubble (October 1998 to March 2000), the NASDAQ crash, the accounting scandal and September 11 attacks (April 2000 to October 2002), the subsequent period leading up to the mortgage crisis (November 2002 to June 2007), the recent financial crisis (July 2007 to December 2008), and the remaining period (January 2009 to December 2010). Within these periods, more patterns of the average manager's performance become manifest, as reported in Table 5. That is, market downturns are matched to significantly large negative alphas (the NASDAQ crash and the recent financial crisis, respectively, correspond to –20.02% p.a. (t-statistic –2.00) and –39.92% p.a. (–1.72)), while market upturns or normal times are mostly matched to significant and positive alphas (the periods before the tech bubble, during the tech bubble, after the bubble crash leading up to the mortgage crisis, and after the recent crisis correspond to 4.86% p.a. (0.71), 23.38% p.a. (2.77), 12.81% p.a. (2.92), and 15.90 % p.a. (1.26), respectively).[21, 22]

[21] Fung et al. (2008) apply two structural breakpoints, LTCM crisis (September 1998) and the NASDAQ crash (March 2000), to their sample between 1995 and 2004. Hesse, Frank, and Gonzalez-Hermosillo (2008) identify subprime turbulence (July 2007) as the structural breakpoint. Ivashina and Sharfstein (2010) define August 2007 to July 2008 and August 2008 to December 2008 as crisis I and crisis II, respectively. To ensure enough observations in each sub-period, I combine the two into one (choosing either July 2007 or August 2007 does not make difference in the results). Also, the NASDAQ crash seems to continue until 2002 because of a series of accounting scandals and the September 11 attacks; therefore, I choose December 2002 as the end of the crash.
(http://en.wikipedia.org/wiki/Stock_market_downturn_of_2002)

The pro-cyclical movement of the average fund's performance may be able to be explained further by incorporating market conditions into the model. Under the conditional model, I allow the market-wide parameters to change over time, while under the unconditional model, I assume the parameters to be constant across the entire sample period. More specifically, each market-wide parameter is set to be a function of instruments, so that it changes with market conditions. Panel C of Table 4 presents the estimates with conditioning information, in which the timing component (0.17% p.a. (t-statistic 0.04)) becomes positive, whereas the selectivity alpha (2.39% p.a. (2.37)) remains similar to its level without conditioning information. Moreover, Figure 3 shows that about 20% of the overall performance during 2008 can be explained by conditioning information. This suggests that without information about economic state, investors would commit the mistakes of using inflated risk exposure to ascribe poor performance to the manager. Furthermore, conditioning information does not appear to affect the selectivity measure.

The change in the average fund's performance with market conditions may also be explained by hedge funds' capital structure. If hedge funds have devices to alleviate investors' running on the funds during crises, they are less likely to be forced to engage in fire-sales. Then managers can maintain their discretionary trading activities with less capital constraints. To investigate the impact of capital constraints on fund mangers' arbitrage activities, I split the sample into two or three sub-samples according to share

[22] We design the estimation method to account for the autocorrelation and heteroskedasticity of the residual terms of the time series; that is, we use the Newey-West covariance matrix with a lag of three, which is why I split the sample this way. Ignoring the time-series characteristics and breaking the sample dichotomically into crisis (the NASDAQ crash and recent financial crisis) and non-crisis (the remaining period) periods, we still have consistent results. That is, –27.34% p.a. (t-statistic –2.51) for the crisis, which represents selectivity alpha of 4.81% (1.80) and timing alpha of -32.15% (3.19)), and 12.16% p.a. (3.34) for the non-crisis, which consists of selectivity alpha of 1.58% (1.74) and timing alpha of 10.58% (2.97).

restrictions such as lock-up periods and redemption-notice periods (equity capital constraints), and average leverage (debt capital constraints) using a TASS snapshot as of April 25, 2012. Then I form a portfolio of going long the top portfolio and short the bottom, the yearly alpha of which is depicted in panels A and B of Figure 4. We can see that those with longer redemption notice periods tend to outperform those with shorter redemption notice periods by 6.23% (2.95) during 2008. Also, those with lockup period clause appear to outperform those without lockup period clause by 2.83% (2.52) during 2008. Overall those with strong share restrictions seem to perform better than those with weak share restrictions as shown in Panels A and B of Table 6, an outcome that appears to be mainly driven by mangers' stock picking skill. Also, we can see that share restrictions played an important role during tech bubble period. But we can also observe the slight drop in performance of the funds with strong share restrictions during 2007. This may suggest that there could have been pre-emptive reaction by investors because of the concave flow-performance relationship in the presence of share restrictions as argued by Ding et al. (2008). Those with leverage tend to perform a little better than those without during the recent financial crisis, as illustrated in panel C of Figure 4. During 2008 it seems that leverage was helpful for improving timing performance.[23]

Another way to think of the large fluctuations in average fund performance with market conditions is to approach them from the forced liquidation story. That is, hedge funds in the face of forced liquidation may prefer to sell off the stocks with low sensitivity to the market return, leaving them with high sensitivity stocks when market

[23] But Ang, Gorovvy, and Inwegen (2011) show that hedge funds keep changing their leverage, which is countercyclical to the leverage of listed financial intermediaries. So the weak evidence may be due to the coarse indicator variable for average leverage.

return plunges. Ben-David, Franzoni, and Moussai (2011), Brown, Carlin, and Lobo (2010), and Scholes (2000) posit that investors prioritize their stocks when facing forced liquidation or during risk management, such as selling off liquid stocks. However, as Panel A of Figure 2 shows, the average hedge fund manager actually reduced its market exposure through their equity holdings during the market downturns, both by selling high beta stocks and buying low beta stocks. But the total exposure was still positive when market return is far below its historical average, so we have negative timing ability. In addition, we can observe that the beta of the stocks purchased by the average fund was highest during the tech bubble.

In contrast, the average hedge fund increased its exposure to the market liquidity during the recent financial crisis, by selling less sensitive stocks and buying more sensitive stocks as shown in Panels B and C of Figure 2. Indeed they exhibit negative liquidity timing ability during crisis although the magnitude is small compared to that of market return timing ability.

In addition, I look at the difference in stock-level liquidity between the stocks bought and sold by the average manager, which is shown in Panel D of Figure 2. To avoid the price impact of trade, I use 12 month prior liquidity level measure. We can see that during 2008Q3, the difference in value-weighted average liquidity between the stocks sold and bought is significantly negative, while the difference in equally weighted average is insignificant. This suggests that those stocks sold a lot are more liquid than those stocks bought a lot. Similar phenomena are observed during 1998Q3 and 2000Q1. Thus, consistent with the previous literature, it seems that liquid stocks are more preferred to be sold off during market downturns.

Overall, it seems that during the second half of 2008, the stocks sold off by the average hedge fund manager can be described as liquid stocks with high sensitivity to market return and low sensitivity to market liquidity compared to the stocks she purchased. In fact, as depicted in Panel E, we can observe that the correlation between liquidity and liquidity beta is negative, and the correlation between liquidity and market beta is positive over the sample period. However, what we can also observe is that the correlation between liquidity and liquidity risk closes to zero during crises, which means that liquidity level and risk becomes more independent. This can be consistent with Sadka and Lou (2011), who argue that liquid stocks can be dangerous during crisis by showing that liquid stocks (stock level) can underperform illiquid stocks during crisis, and the performance of stocks during the crisis can be better explained by historical liquidity beta than stock level liquidity.

Another possible story for the pro-cyclical movement of the average fund performance is that 13F does not provide complete picture of all holdings, so we cannot observe their other positions which can possibly deliver positive alpha. Other positions can include short selling and derivatives. If such strategies are used, we would expect the overall market exposure of the average fund to be negative or small during the market pullbacks, and liquidity exposure to be positive or big during the market liquidity dry-ups. To investigate this, I form an equally weighted portfolio of the funds whose managers fall into the final sample in this study using hedge fund returns data from TASS, and then employ the returns-based performance measure following Treynor and Mazuy (1966) and Cao et al. (2012). That is, the market-, liquidity- , and volatility timing are measured as the coefficient estimates of β, γ, and θ, respectively, in the following regression:

$$eret_{p,t} = \alpha + \beta MKTRF_t^2 + \gamma MKTRF_t \times LIQ_t^d + \theta MKTRF_t \times VIX_t^d + FH7\ factors,$$

where $eret_{p,t}$ is the portfolio return in excess of risk-free rate at month t, $\mathrm{MKTRF_t}$ is the market excess return in month t, LIQ_t^d the demeaned traded Amihud liquidity factor, VIX_t^d the demeaned VIX (measure of implied volatility of S&P 500 index options), and $FH7\ factors$ the Fung and Hsieh seven factors, which include three trend following factors (bond (PTFSBD), currency (PTFSFX), and commodity (PTFSCOM)), two equity-oriented risk factors (equity market (MKTRF), size spread factor (SMB)), and two bond-oriented risk factors (bond market (YLDCHG), credit spread factor (BAAMTSY)).[24] Using 36-month rolling window, I find that the average fund exhibits positive market return timing and negative liquidity- and volatility timing ability during the recent financial crisis, but overall I do not find evidence of timing abilities as shown in Panel A of Figure 5 and Panel A of Table 7.

To examine whether the use of derivatives makes any difference in performance dynamics, I break down the sample according to the hedge fund managers' use of derivatives, which is proxied by the average of the TASS "Derivatives" indicator across individual funds for each manager. The difference in alpha between hedge fund managers who do and do not use derivatives seems to be a little counter-cyclical, as illustrated in Panel C of Figure 5, which suggests the possibility that derivatives users use long equity positions for hedging purposes.[25]

[24] I thank Prof. Hsieh for providing the data on his website: http://faculty.fuqua.duke.edu/~dah7/HFData.htm

[25] But Aragon and Martin (2012) show that there is a big gap in derivative indicator between their hand-collected 13F holdings information and the snapshot from TASS. So the weak evidence can be driven by this information gap.

In summary, conditioning information, equity capital constraints, and priority of the stocks sold in the face of forced liquidation can partly explain the time-variation of the average fund performance with market conditions. However, debt capital constraints, and use of derivatives do not seem to account for the performance dynamics.

Another plausible explanation for the average hedge fund manager's lack of skill is that, as Griffin and Xu (2009) mentioned, hedge funds employ strategies that only work under certain market conditions, such as during the tech bubble. Brunnermeier and Nagel (2004) examine hedge funds' 13F holdings from April 1998 to December 2000, and show that hedge funds adjust their positions in high price-to-sales stocks in a timely fashion to capture the upturn and avoid the downturn during the technology bubble. However, I find evidence consistent with Brunnermeier and Nagel (2004) only in terms of selectivity skill.[26]

Relative to overall timing and performance, the selectivity alpha of the average fund tends to be stable over time. It does not plummet during market downturns, and is even positive during those periods.

Although the average fund performance is weak, skill can still exist at the individual fund level. Figure 8 provides the distribution of individual funds' alphas. The normal distribution does not appear to fit well with the alpha distribution of individual funds. Overall, the alpha distribution is more peaked (has higher kurtosis) than normal and so tends to have slightly heavy tails on both sides. Most alpha distributions appear to be skewed to the left except for selectivity alpha.

[26] Using the same sample period as theirs, I find that the SDF-based selectivity alpha is 5.42% p.a. (t-statistic 1.54) for the equally weighted portfolio, while the timing alpha is only 0.32% (0.03).

To assess the significance of the cross-sectional statistics of ability, I rely on a bootstrap procedure following Kosowski et al. (2006) and Jiang, Yao, and Yu (2007). The reasons are as follows: first, we cannot just rely on t-statistics to determine the statistical significance at the individual fund level as we do analysis at the aggregate level. This is because to investigate ranked managers, we need to consider order statistics, which means that we need to figure out the joint distribution of over 600 managers' skill probability distribution. Thus, if we examine funds' ability based on the t-statistics, we can have some funds with significant positive ability just by sample variation, regardless of their actual ability. Second, we cannot assume the ability is identically and independently distributed (i.i.d.) across funds. Hedge funds can hold significantly different stocks or similar stocks according to their investment strategies, which means that their ability can be heterogeneous and correlated. Also, the life spans of funds do not necessarily overlap with one another, and the number of sample changes over time. Finally, the finite sample distributions for the cross-sectional statistics can be different from their asymptotic counterparts. To address these issues, I follow the prior studies and rely on a bootstrap analysis that depends on the ex-post empirical distribution rather than the ex-ante parametric distributions.

The bootstrapping procedure obtains the distribution of a particular cross-sectional statistic (say, top 10^{th} manager's alpha) under the null hypothesis of no ability, and then compares it to the actual statistic to determine the statistical significance level for the statistic. To conduct the bootstrap analysis, I first generate a large number of cross-sections (here, 1,000 iterations) of individual funds' alphas under the assumption of no ability. To do so, I fix the stocks' market and liquidity betas, and portfolio weights, but instead randomly sample with replacement the idiosyncratic stock returns, market returns, liquidity risk, and risk-free rate, independently, to generate a hypothetical dataset. [27] [28] Then I compute alphas for each manager to generate one hypothetical cross-section. This can be called the 1st iteration. We do the same procedures until we get the 1,000th iteration. By doing so, we can generate 1,000 cross-sections of alphas under the assumption of no ability. For example, suppose that I want to know whether or not the top 10th manager's alpha is from luck. Then I pick the top 10th alpha from each of the 1,000 hypothetical cross-sectional distributions, and compare the 1,000 top 10th hypothetical alphas with the actual top 10th manager's alpha. If the actual alpha is consistently higher than the corresponding hypothetical alpha, then we cannot say that the manager's alpha is from luck. So the bootstrapped p-values for alpha and t-statistic, respectively, can be computed by

$$p_{value,\alpha} = \frac{\sum_i 1\{\alpha_{Hypothetical,\ i} > \alpha_{Actual}\}}{1{,}000}, \text{ or } p_{value,t} = \frac{\sum_i 1\{t\text{−}stat_{Hypothetical,\ i} > t\text{−}stat_{Actual}\}}{1{,}000},$$

where $1\{x\}$ is an indicator variable having value of 1 if the statement x is correct, and 0 otherwise.[29] That is, a low value of p (close to zero) implies that the actual alpha is consistently higher than its bootstrapped values and the evidence of ability, while a high

[27] I use different seed numbers for each factor.

[28] Alternatively, one could randomly select holdings positions for each fund. However, it is challenging because managers hold different stocks over time and stocks exist only for some periods. Also, considering that hedge fund managers' investment strategies are correlated with each other, keeping the actual holdings information fixed can preserves the covariance structure of the fund's market exposure (strategy) with correlated fund betas.

[29] t-statistic is a pivotal statistic, which has some superior statistical properties when constructing bootstrapped cross-sectional distributions, since it scales alpha by its standard error, which tends to be larger for short-lived funds for funds that take higher levels of risk. In addition, it is related to the Treynor and Black (1973) appraisal ratio, which is commonly used by practitioners to rate fund managers, and is prescribed by Brown et al. (1992) for helping to mitigate survival bias problems. Thus, the distribution of bootstrapped t-statistics in the tails is likely to exhibit better properties than the distribution of bootstrapped alpha estimates in the region.

value of p (close to one) implies that the estimated timing measure is consistently lower than its bootstrapped values and thus evidence of luck.

Table 8 reports the results of bootstrap analysis for alphas and t-statistics. We can see that even top managers' skills are likely from luck (we have only three exceptions in the t-statistics case: managers of the top selectivity skill, the top and top 90th volatility skill). This is in contrast with Kosowski, Naik, and Teo (2007), who study hedge fund performance using returns data and bootstrap and Bayesian approach, and conclude that top hedge fund performance cannot be explained by luck. This may suggest that the performance effect of market conditions outweighs that of randomness.

Table 9 reports the performance persistence of individual funds. Following Griffin and Xu (2009), I examine the performance persistence in two ways: based on the prior year's performance and on the entire performance history. First, for each year, I sort managers into quintiles according to their previous year's alphas, requiring a full 12 months of observations.[30] Then I form an equally weighted portfolio for each quintile, and estimate alphas of the current year for each quintile portfolio. To ensure that I have enough funds for ranking, the evaluation period starts in 1997. Panel A of Table 9 presents alphas for each quintile in which the portfolio is rebalanced every year according to the previous year's ranking, and is held for one year. Also reported is the performance difference between the top and the bottom portfolios to examine the performance persistence. We can observe weak performance persistence for total alpha (3.44% p.a. (1.48)), which can be decomposed into positive selectivity component (3.69% p.a. (2.20))

[30] Conducting the same experiments with the previous 2 years' observations requiring at least 15 observations yields slightly weaker results than conducting the experiments with 1 year of observations, but selectivity skill still exhibit persistence.

and the negative timing component (–0.25% p.a. (-0.13)). When ranking is based on the prior year's selectivity skill, the selectivity component again appears to be persistent (3.92% p.a. (2.11)), whereas the timing component (–0.58% p.a. (-0.42)) reduces the overall performance (3.34% p.a. (1.43)). Timing ability does not exhibit persistence. These results are in line with the unstable movement of timing alpha and the relatively stable movement of selectivity alpha, as shown in the portfolio level analysis. Next I investigate the performance persistence based on the entire history, taking into account the fact that investors generally base their decisions on the entire history rather than only the last year's performance. The results shown in panel B of Table 9 are weaker than those based on the prior year's performance. We can view this finding as supporting the rational model of Berk and Green (2004). In their model, managers have differential abilities to generate risk-adjusted returns but face decreasing returns to scale in deploying their ability; thus investors' rational provision of capital to funds with superior skill results in zero risk-adjusted, after-fee returns to the investors. Ignoring the statistical significance, the spread portfolio based on the prior year's market timing delivers the highest total alpha (3.89% p.a. (1.81)). In contrast, the portfolio formed according to the prior year's volatility timing yields the worst timing ability in the following year (-4.24% p.a. (-1.47)). For the entire history case, the portfolio based on the historical total performance performs the best.

This paper introduces liquidity timing ability using a holdings-based measure for the first time. However, I do not detect any significant liquidity timing ability both at the portfolio level and at the individual fund level. Cao et al. (2012) investigate liquidity timing at the individual fund level, relying on a returns-based measure and bootstrap analysis, and argue that managers of equity-oriented hedge funds can time the market liquidity by adjusting the funds' exposure based on their forecasts about market liquidity conditions.[31] The results are consistent at the aggregate level in that we both do not find significant evidence on liquidity timing ability. But the difference at the individual fund level may be due to the fact that they assume liquidity as one dimension of market conditions and measure the liquidity timing ability as the covariance between market beta and liquidity risk, while I assume the two factors play independent roles in asset pricing, and measure it as the covariance between liquidity beta and liquidity risk.[32] Another possibility is that managers have little information about future unexpected liquidity risk, or they time the market liquidity with high frequency.[33]

I also investigate whether hedge fund managers can time market liquidity even if liquidity risk is predictable based on publicly available information. Pesaran and Timmermann (1995) examine whether the predictability of U.S. stock returns could have been exploited by investors, and find that the predictive power of various economic

[31] By replicating Cao et al. (2012) and observing that a larger proportion of hedge funds subject to 13F filings lie on the right-hand side of the timing ability distribution (their Table 4), I confirm that different datasets do not drive the different results.

[32] However, using their returns-based measure, both the average fund constructed from their sample and the average fund from mine do not exhibit liquidity timing ability. When I change only the PS liquidity level to the PS traded liquidity risk factor (or PS non-traded liquidity risk factor) in their returns-based setting, the results become weaker.

[33] Under the assumption that managers possess no special skill, the holdings-based measure can avoid the interim-trading bias raised in the returns-based measure, because we can use ex-ante information, which is not contaminated by subsequent trading activities using public information between returns-reporting dates. However, under the assumption that managers possess superior ability, the holdings-based measure has less statistical power than the returns-based measure, because of the lower frequency of the data (quarterly vs. monthly). Based on the existing literature, to resolve the loss of statistical power issue, I could use publicly available high-frequency (daily) data, such as market returns and stocks returns or conditioning information, employ simulation or bootstrap analysis to show the superiority of holdings-based measure over the returns-based measure (Ferson and Khang, 2002; Goetzmann, Ingersoll, and Ivkovich, 2000; Jiang, Yao, and Yu, 2007). Future research could conduct the experiment using daily liquidity-factor data. In addition, Busse (1999) and Bollen and Busse (2001) use proprietary high-frequency (daily) fund-return data. Ferson, Henry, and Kisgen (2006) exploit the specific feature of SDF such that SDF for term-structure models can be represented as simple exponential functions of term-structure factors.

factors over stock returns changes through time. Based on the evidence from early studies they select a benchmark set of regressors from which an investor can select predictors of market returns in “real time.” The set consists of a constant as well as nine regressors including the dividend yield, earnings-price ratio, 1-month T-bill rate, 12-month T-bond rate, year-on-year inflation, year-on-year rate of change in industrial output, and year-on-year growth rate in the narrow money stock.

To my knowledge, existing studies do not examine the predictability of market-wide liquidity. Therefore I establish a base set of potential forecasting variables from Welch and Goyal’s (2007) study of the predictors of the equity premium. I choose the nine variables which are most highly correlated with the traded liquidity risk factor over the period of January 1984 to December 2011. Namely, lagged traded liquidity risk factor, lagged book-to-market ratio (the ratio of book value to market value for the Dow Jones Industrial Average), lagged Treasury-bill rate (3-Month Treasury), lagged long-term yield (long-term government bond yield), lagged inflation rate(Consumer Price Index), lagged stock variance (sum of squared daily returns on the S&P 500), lagged CRSP spread value-weighted index, lagged dividend price ratio (the difference between the log of dividends and the log of prices), and lagged earnings price (the difference between the log of earnings and the log of prices).

For each month, I run OLS regressions of the traded market-wide liquidity factor on all the possible combinations of nine potential forecasting variables using the prior 60 months of observations. Thus, for each month, I run 512 (=2^9) regressions and select the best forecasting equation for the month based on the statistical model selection criteria such as Akaike’s Information Criterion (AIC), Schwarz’s Bayesian Information Criterion

(BIC), and R-square (R^2). Based on the estimated coefficients from the best forecasting equation, I make the one-month ahead prediction of liquidity factor. The AIC and BIC criteria are likelihood-based and assign different weights to the "parsimony" and "fit" of the models. The "fit" is measured by the maximized value of the log-likelihood function, and the "parsimony" by the number of freely estimated coefficients.

Following Pesaran and Timmermann (1995), I examine the fit of the recursive forecasts by looking at the recursively computed squared correlation coefficient between the recursive forecasts obtained under the different model selection criteria and the actual traded liquidity risk portfolio return, which are reported in Figure 9. Although the traded liquidity risk portfolio return seems to have been weakly predictable during the recent financial crisis based on publicly available information and rolling model selection criteria, overall it does not seem to be predictable. Also, if we just look at whether the sign of actual liquidity and forecast coincide, we have the same sign for slightly more than 50% of months (52%-55%) for all model selection criteria over the period (January 1989 to December 2011) and the sample period (January 1995 to December 2010). The lack of predictability in the traded liquidity risk factor based on public information shed light on the lack of liquidity timing ability among hedge fund managers. In particular, the evidence here helps exclude the puzzling scenario in which managers do not exhibit timing ability even though liquidity returns are predictable.

Moreover as in the case of Pesaran and Timmermann (1995), the best predictors seem to change over time as shown in Panel D of Figure 9, thereby highlight the importance of a dynamic model for model selection. Overall it seems that CRSP S&P value-weighted index, stock variances, and book-to-market ratio are the best predictors over the period of January 1989 through December 2011, while the lagged liquidity and dividend to price ratio are more important during the earlier period, and the Treasury bill rate and Long-term yield are more important during the later period.

Chapter 6

CONCLUSION

In this paper, I evaluate hedge fund managers' stock picking skill and various timing abilities – market return, volatility, and liquidity – using 13F equity holdings data and a stochastic discount factor (SDF) model built on Ferson and Mo (2012). Consistent with Griffin and Xu (2009), I find weak evidence of hedge fund managers' capacity for informed trading.[34] However, by examining the time-variation and decomposition of performance of the average hedge fund manager, I shed additional light on why we do not find strong evidence to support the conventional view of hedge fund managers' superiority.

At the aggregate level, I find that the weak evidence is driven by the large fluctuations in overall performance, which are determined primarily by the timing component, which in turn largely depends on market conditions. In contrast, selectivity skill exhibits relatively stable patterns over time, and does not seem to be as affected by market conditions. Moreover, I show that the conditioning information, equity capital constraints, and priority in stocks to liquidate can partly explain the time-variation of performance with market conditions. However, debt capital constraints, and use of derivatives do not seem to account for the performance dynamics.

Also, at the individual fund level, using bootstrap analysis I show that even the top managers' alphas cannot be separated from luck, which is in contrast with the

[34] Using one of Griffin and Xu's (2009) sub-sample periods overlapping with mine, 1995-2004, I find that the GMM estimation for the equally weighted portfolio constructed from my sample gives total alpha of 2.22% p.a. (t-statistic 0.44), selectivity alpha of 2.42% p.a. (1.67), and timing alpha of -0.19% p.a. (-0.04).

existing evidence based on hedge fund returns data. Also, I find that there is a short-term persistence in hedge fund managers' performance.

For future research it would be interesting to conduct the analysis with high frequency data, and more refined data.

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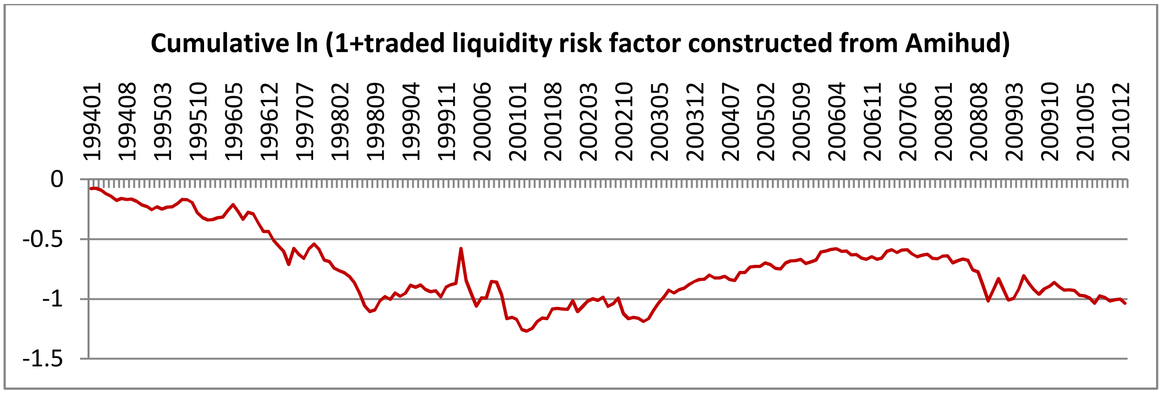
APPENDIX I

FIGURES AND TABLES

Figure 1. Cumulative traded liquidity risk factor: Pastor and Stambaugh vs. Amihud.

The top one depicts the cumulative traded monthly liquidity factor constructed from Amihud (2002), and the bottom one depicts that of Pastor and Stambaugh (2003). I cumulate the logarithm of one plus traded liquidity risk portfolio return. Monthly traded Pastor and Stambaugh measure is downloaded from Prof. Stambaugh's homepage. Their measure is computed as the return to the spread portfolio sorted on liquidity innovations in their paper. The traded Amihud liquidity measure is computed as the return to the spread portfolio based on liquidity sensitivity. That is, each month stocks are sorted into deciles based on their liquidity sensitivity, and then a spread portfolio is formed by buying the top decile portfolio (the most sensitive group) and selling the bottom decile portfolio (the least sensitive group). Liquidity sensitivity is computed as the coefficient estimate in the regression of stock return on market excess return and market-wide liquidity measure. For each month, I use prior 60 months' observations requiring at least 24 months' observations to run regressions. Monthly market return, risk-free rate, and stock information are from CRSP. Market-wide liquidity measure is computed as the residual of the regression of monthly Amihud liquidity measure on two lagged monthly Amihud liquidity measures. I use 60 months' observations to run this regression. Monthly Amihud liquidity measure is computed as the monthly average of daily liquidity measure, where daily liquidity measure is defined as minus one multiplied by the daily ratio of stock return over dollar volume following Amihud (2002).


Cumulative ln (1+traded liquidity risk factor constructed from Amihud)
199401 199408 199503 199510 199605 199612 199707 199802 199809 199904 199911 200006 200101 200108 200203 200210 200305 200312 200407 200502 200509 200604 200611 200706 200801 200808 200903 200910 201005 201012
0
-0.5
-1
-1.5

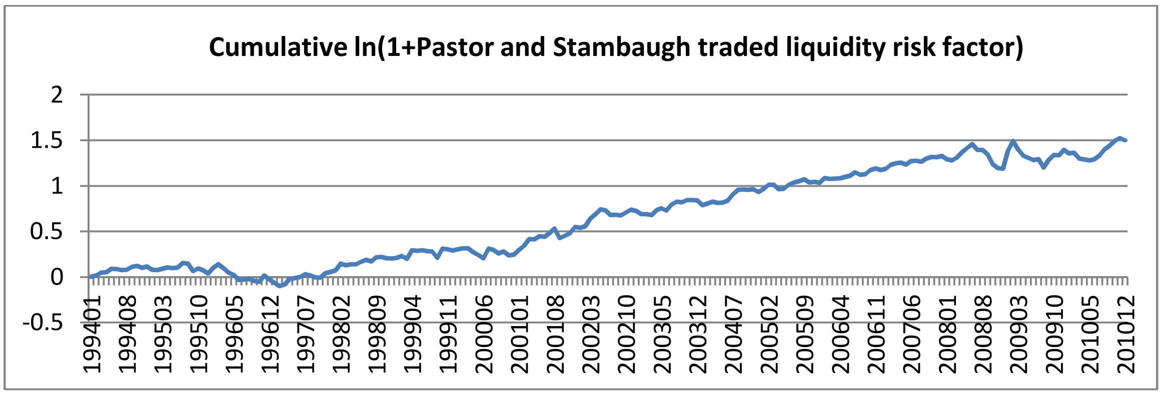

Cumulative ln(1+Pastor and Stambaugh traded liquidity risk factor)
2
1.5
1
0.5
0
-0.5
199401 199408 199503 199510 199605 199612 199707 199802 199809 199904 199911 200006 200101 200108 200203 200210 200305 200312 200407 200502 200509 200604 200611 200706 200801 200808 200903 200910 201005 201012

Table 1. Factors.

Panel A. Summary statistics of the monthly market return in excess of the risk-free rate and the traded Amihud liquidity factor over the period 1995 January to 2010 December. The traded Amihud liquidity measure is computed as the return to the spread portfolio based on liquidity sensitivity. That is, each month stocks are sorted into deciles based on their liquidity sensitivity, and then a spread portfolio is formed by buying the top decile portfolio (the most sensitive group) and selling the bottom decile portfolio (the least sensitive group). Liquidity sensitivity is computed as the coefficient estimate in the regression of stock return on market excess return and market-wide liquidity measure. For each month, I use prior 60 months' observations requiring at least 24 months' observations to run regressions. Monthly market return, risk-free rate, and stock information are from CRSP. Market-wide liquidity measure is computed as the residual of the regression of monthly Amihud liquidity measure on two lagged monthly Amihud liquidity measures. I use 60 months' observations to run this regression. Monthly Amihud liquidity measure is computed as the monthly average of daily liquidity measure, where daily liquidity measure is defined as minus one multiplied by the daily ratio of stock return over dollar volume following Amihud (2002). Monthly market return, risk-free rate, and stock information are from CRSP.

	n	mean	std	min	q1	Med	q3	max
Market	192	0.0056	0.0480	-0.1855	-0.0232	0.0150	0.0364	0.1104
Liquidity	192	-0.0024	0.0583	-0.2360	-0.0314	0.0004	0.0228	0.3416

Panel B. Estimates of the market-wide parameters under unconditional model. I estimate the parameters for the equations (6a) to (6c) subject to (6g) using the GMM method with the Newey-West covariance matrix of three lags.[1] Here, I assume the parameters are fixed over the sample period 1995 January and 2010 December, and I use the monthly risk-free rate, market excess return and traded Amihud liquidity measure as the primitive assets.

Parameter	Estimate	StdErr	t-value	Probt	DF
a	1.0171	0.0222	45.74	<.0001	191
b_M	2.9383	1.9348	1.52	0.1305	191
b_L	-1.3921	1.2689	-1.1	0.2740	191
μ_M	0.0056	0.0038	1.48	0.1418	191
μ_L	-0.0024	0.0040	-0.59	0.5539	191

Panel C. Mean of the SDF. Since we assume risk-free portfolio is a primitive asset, it satisfies the asset pricing formula, so we have the expected value of SDF as the inverse of the expected value of gross risk free rate. I use monthly risk-free rate over the sample period 1995 January to 2010 December, which are obtained from CRSP.

	n	$E(m)$
m	192	0.9973

[1] The table of 25 coefficient estimates for the parameters under conditional model is available upon request.

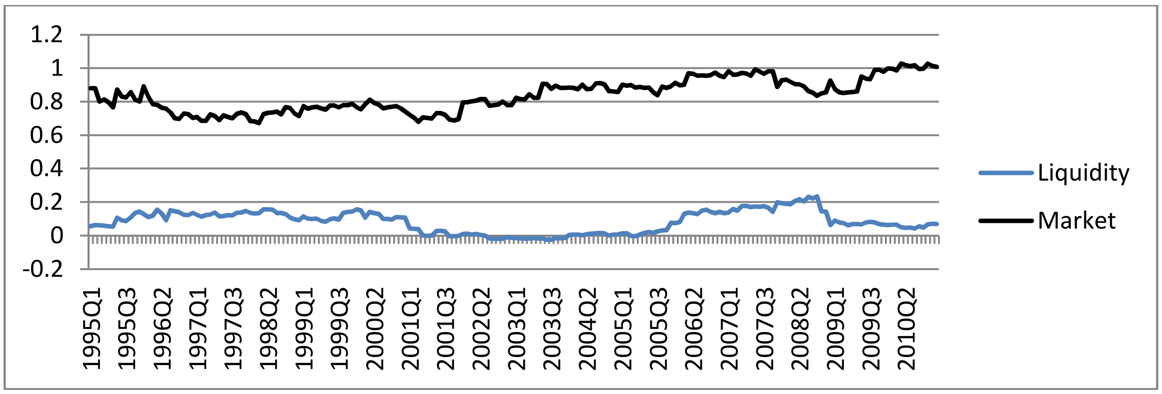
Table 2. Average fund's exposure

The summary statistics of the average fund's monthly exposure to the market excess return, the traded Amihud liquidity measure, and the idiosyncratic risks. The exposure is the weighted average of betas or idiosyncratic risk of individual stocks held by the average fund, with prior quarter-end holdings as weights. I obtain individual stock betas using the regression of stock excess return on market excess return and traded Amihud liquidity risk factor, and the previous 60 months of observations requiring at least 24 months of observations.

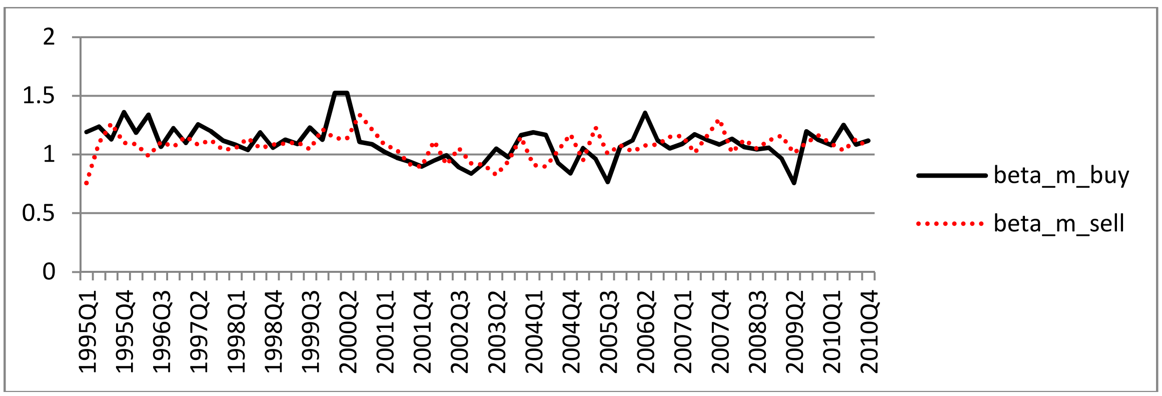
	N	mean	std	min	q1	med	q3	max
Market ($x'\beta_M$)	192	0.8376	0.0963	0.6711	0.7614	0.8328	0.9046	1.0273
Liquidity ($x'\beta_L$)	192	0.0829	0.0651	-0.0260	0.0146	0.0903	0.1347	0.2347
Idiosyncratic risk ($x'v$)	192	0.0021	0.0094	-0.0304	-0.0030	0.0020	0.0077	0.0348

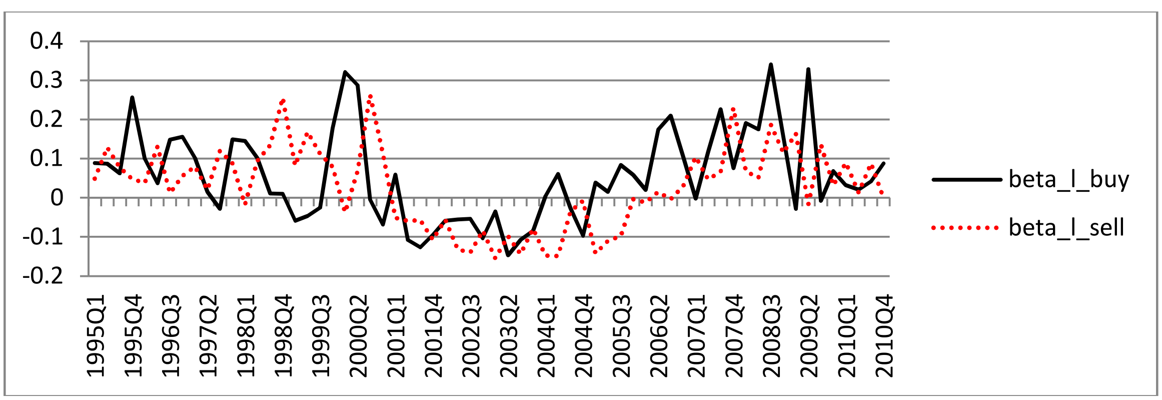
Figure 2. Average fund's exposure.

Panel A. The average fund's monthly exposure to the market excess return and the traded Amihud liquidity risk. The exposure is the weighted average of betas or idiosyncratic risk of individual stocks held by the average fund, with prior quarter-end holdings as weights. I obtain individual stock betas using the regression of stock excess return on market excess return and traded Amihud liquidity risk factor, and the previous 60 months of observations requiring at least 24 months of observations



Panel B. The weighted average of the betas for the stocks bought and sold by the average fund. The top one depicts the time-variation of market betas for the stocks bought and sold by the average manager for each month. The bottom one depicts the change in liquidity betas for the stocks bought and sold by the average manager over the sample period 1995-2010. For each quarter, if the number of shares for a stock increased from the prior quarter, the stock is defined as "bought;" otherwise as "sold." Stocks that are newly introduced to the current quarter and those that are no longer held in the current quarter are classified as "bought" and "sold" stocks, respectively. I compute the weight as the absolute value of the change in shares multiplied by the share price of the prior quarter-end. I use the prior quarter-end price to reflect the actual trading rather than price changes.



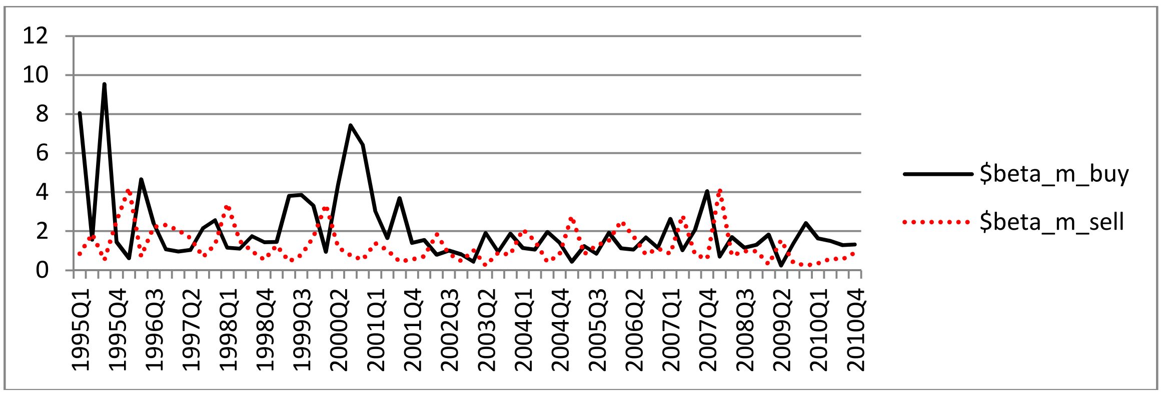


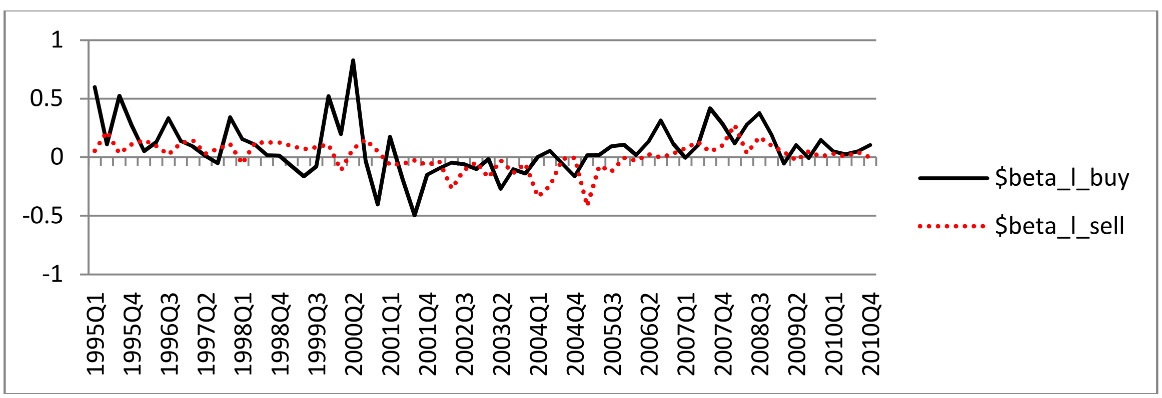
Reported are the t-test results for the difference in means of the betas of the stocks sold and bought. I report the results only for the last quarter of each year to save space. The top one documents the average market betas for the stocks bought and sold, the beta difference, and its t-statistics. The bottom one reports the average liquidity betas for the stocks bought and sold, the beta difference, and respective t-statistics. The t-statistics are computed under the assumption that the variances of betas of the stocks bought and sold are different.

β_{Market}	1995Q4	1996Q4	1997Q4	1998Q4	1999Q4	2000Q4	2001Q4	2002Q4	2003Q4	2004Q4	2005Q4	2006Q4	2007Q4	2008Q4	2009Q4	2010Q4
Sell	1.0987	1.0662	1.0370	1.0855	1.2159	1.2122	0.8941	0.9241	1.1497	1.1714	1.0780	1.1489	1.3017	1.1198	1.1600	1.0590
Buy	1.3596	1.2242	1.1179	1.0566	1.1247	1.0870	0.8962	0.8355	1.1643	0.8383	1.0652	1.0529	1.0856	1.0582	1.1234	1.1180
Sell - Buy	-0.2609	-0.1581	-0.0808	0.0288	0.0913	0.1252	-0.0021	0.0886	-0.0145	0.3331	0.0128	0.0960	0.2161	0.0616	0.0365	-0.0590
t-statistic	-20.97	-11.69	-8.70	3.76	10.82	11.83	-0.20	7.85	-0.89	24.37	0.89	7.33	15.75	6.96	3.44	-6.70

$\beta_{liquidity}$	1995Q4	1996Q4	1997Q4	1998Q4	1999Q4	2000Q4	2001Q4	2002Q4	2003Q4	2004Q4	2005Q4	2006Q4	2007Q4	2008Q4	2009Q4	2010Q4
Sell	0.0477	0.0555	0.0875	0.2556	0.0792	0.1125	-0.1073	-0.0844	-0.0789	-0.0078	-0.0037	0.0299	0.2293	0.1151	0.0316	-0.0018
Buy	0.2564	0.1561	0.1494	0.0098	0.1782	-0.0682	-0.0949	-0.1036	-0.0852	-0.0973	0.0587	0.1053	0.0758	0.1546	0.0684	0.0875
Sell-Buy	-0.2087	-0.1006	-0.0619	0.2458	-0.0990	0.1807	-0.0124	0.0191	0.0063	0.0894	-0.0624	-0.0754	0.1535	-0.0395	-0.0368	-0.0893
t-statistic	-16.11	-8.14	-8.62	36.17	-10.64	20.19	-1.99	3.51	1.05	14.10	-8.84	-8.89	14.56	-3.72	-4.27	-12.80

Panel C. The dollar amount of betas of the stocks bought and sold by the average manager ($ billions). The top one depicts the dollar amount of market betas for the stocks bought and sold by the average manager. The bottom one depicts the dollar amount of liquidity betas for the stocks bought and sold by the average manager. The dollar amount of beta is the weighted sum of betas of the stocks bought and sold by the average fund, with weight as the absolute value of the change in shares multiplied by the share price of the prior quarter-end. I use the prior quarter-end price to reflect the actual trading rather than price changes. For each quarter, if the number of shares for a stock increased from the prior quarter, the stock is defined as "bought;" otherwise as "sold." Stocks that are newly introduced to the current quarter and those that are no longer held in the current quarter are classified as "bought" and "sold" stocks, respectively



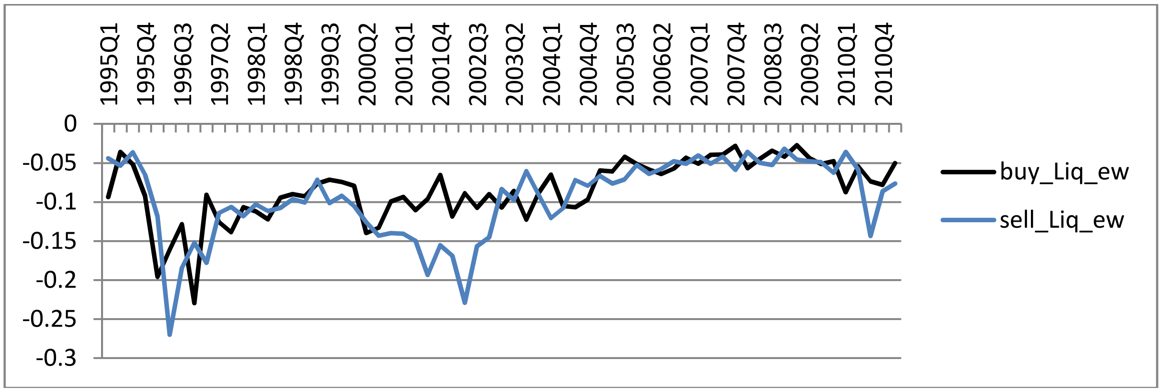


Reported are the t-test results for the difference in means of the dollar amount betas multiplied by the number of stocks during the corresponding quarter. I report the results only for the last quarter of each year to save space. The top one documents the average dollar amount of market betas for the stocks bought and sold, the beta difference, and its t-statistics. The bottom one reports the average dollar amount of liquidity betas for the stocks bought and sold, the beta difference, and its t-statistics. The t-statistics are computed under the assumption that the variances of betas of the stocks bought and sold are different.

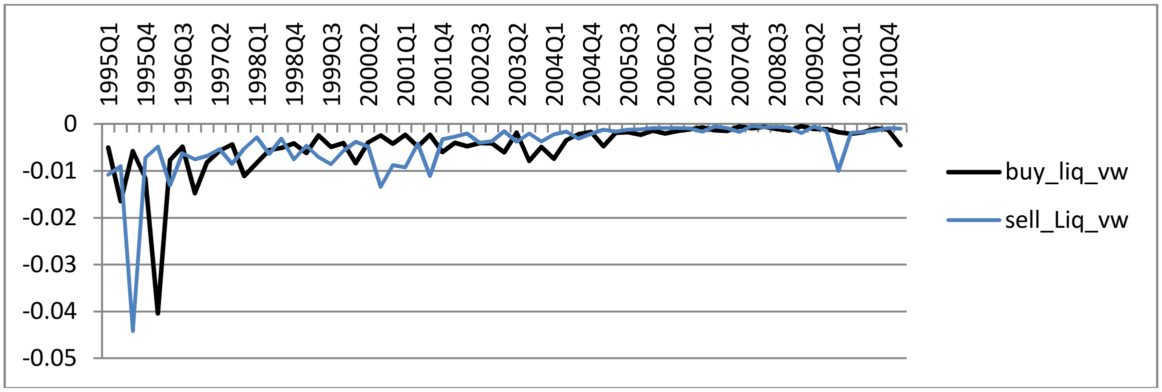
β_{Market}	1995Q4	1996Q4	1997Q4	1998Q4	1999Q4	2000Q4	2001Q4	2002Q4	2003Q4	2004Q4	2005Q4	2006Q4	2007Q4	2008Q4	2009Q4	2010Q4
Sell	2.5158	2.3110	1.3162	0.5326	1.6900	0.5285	0.5536	0.4683	0.8044	0.8079	1.5121	1.1107	0.5788	0.9684	0.2340	0.8911
Buy	1.4541	1.0798	2.5573	1.4331	3.2980	6.4414	1.4083	0.8061	1.8824	1.4057	1.9216	1.1409	4.0541	1.3093	2.4139	1.3269
Sell - Buy	1.0616	1.2312	-1.2411	-0.9006	-1.6080	-5.9129	-0.8547	-0.3378	-1.0779	-0.5978	-0.4095	-0.0302	-3.4753	-0.3409	-2.1799	-0.4358
t-statistic	6.22	9.04	-5.80	-8.50	-4.71	-12.43	-6.55	-5.24	-3.15	-3.71	-2.35	-0.32	-17.42	-3.27	-22.83	-5.36

$\beta_{liquidity}$	1995Q4	1996Q4	1997Q4	1998Q4	1999Q4	2000Q4	2001Q4	2002Q4	2003Q4	2004Q4	2005Q4	2006Q4	2007Q4	2008Q4	2009Q4	2010Q4
Sell	0.1092	0.1203	0.1110	0.1254	0.1100	0.0490	-0.0664	-0.0428	-0.0552	-0.0054	-0.0052	0.0289	0.1020	0.0995	0.0064	-0.0015
Buy	0.2742	0.1377	0.3417	0.0133	0.5220	-0.4039	-0.1490	-0.0999	-0.1376	-0.1631	0.1059	0.1140	0.2829	0.1913	0.1469	0.1039
Sell-Buy	-0.1651	-0.0174	-0.2307	0.1120	-0.4120	0.4530	0.0826	0.0571	0.0825	0.1577	-0.1111	-0.0852	-0.1809	-0.0918	-0.1405	-0.1054
t-statistic	-2.40	-0.33	-5.41	4.52	-3.46	3.88	2.11	3.05	2.09	4.08	-2.29	-2.86	-2.32	-1.37	-3.42	-4.09

Panel D. The liquidity of the stocks bought and sold by the average manger. The stock level liquidity is measured as the monthly average of the daily liquidity measure which is minus one multiplied by the daily ratio of absolute value of stock return to dollar volume following Amihud (2002). The top one depicts the time-variation of equally weighted average of liquidity for the stocks bought and sold by the average manager for each month over the sample period 1995-2010. The bottom one depicts the value-weighted average liquidity for the stocks bought and sold by the average manager. To measure current quarter's monthly stock level liquidity I use prior year's stock price and volume to avoid the impact of trading. For each quarter, if the number of shares for a stock increased from the prior quarter, the stock is defined as "bought;" otherwise as "sold." Stocks that are newly introduced to the current quarter and those that are no longer held in the current quarter are classified as "bought" and "sold" stocks, respectively. I compute the weight as the absolute value of the change in shares multiplied by the share price of the prior quarter-end. I use the prior quarter-end price to reflect the actual trading rather than price changes.



1995Q1
1995Q4
1996Q3
1997Q2
1998Q1
1998Q4
1999Q3
2000Q2
2001Q1
2001Q4
2002Q3
2003Q2
2004Q1
2004Q4
2005Q3
2006Q2
2007Q1
2007Q4
2008Q3
2009Q2
2010Q1
2010Q4
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
buy_Liq_ew
sell_Liq_ew



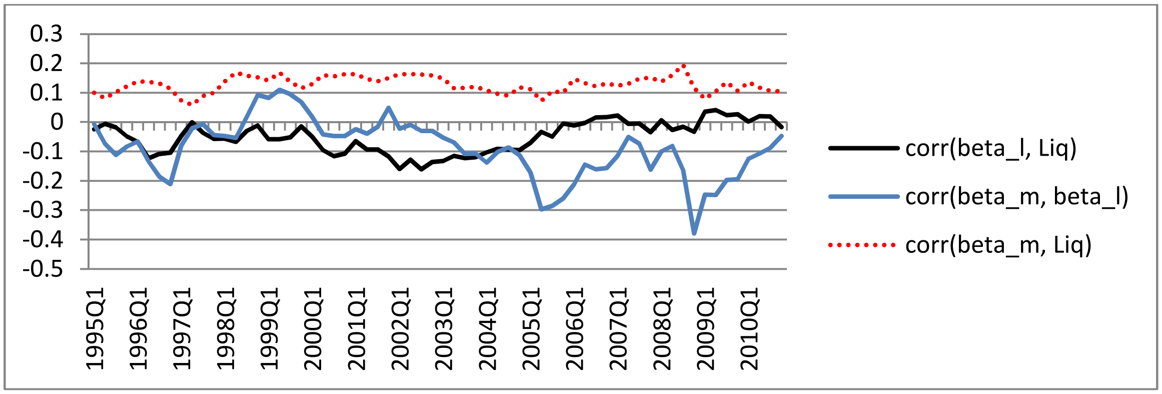
1995Q1
1995Q4
1996Q3
1997Q2
1998Q1
1998Q4
1999Q3
2000Q2
2001Q1
2001Q4
2002Q3
2003Q2
2004Q1
2004Q4
2005Q3
2006Q2
2007Q1
2007Q4
2008Q3
2009Q2
2010Q1
2010Q4
0
-0.01
-0.02
-0.03
-0.04
-0.05
buy_liq_vw
sell_Liq_vw

Reported are equally weighted (left) and value-weighted (right) quarterly average of the monthly liquidity of the stocks bought and sold by the average manager, the mean difference in liquidity between the stocks sold and bought, and its statistical significance. I use 12 months' prior liquidity measure for the current month.

EW	sell	buy	sell-buy	tValue	Probt
1998Q3	-0.1073	-0.0943	-0.0130	0.89	0.3748
1998Q4	-0.0964	-0.0898	-0.0066	-4.73	<.0001
1999Q1	-0.1007	-0.0929	-0.0078	-2.76	0.0059
1999Q2	-0.0716	-0.0765	0.0049	-3.72	0.0002
1999Q3	-0.1012	-0.0713	-0.0299	1.33	0.1823
1999Q4	-0.0921	-0.0742	-0.0180	-0.96	0.3363
2000Q1	-0.1050	-0.0792	-0.0258	-4.11	<.0001
2000Q2	-0.1257	-0.1398	0.0141	-5.15	<.0001
2000Q3	-0.1432	-0.1329	-0.0103	-3.98	<.0001
2000Q4	-0.1398	-0.0994	-0.0404	-7.62	<.0001
2001Q1	-0.1406	-0.0936	-0.0470	-10.34	<.0001
2001Q2	-0.1497	-0.1105	-0.0393	-4.41	<.0001
2001Q3	-0.1935	-0.0960	-0.0976	-11.09	<.0001
2001Q4	-0.1552	-0.0655	-0.0896	-4.60	<.0001
2002Q1	-0.1688	-0.1184	-0.0504	-5.44	<.0001
2002Q2	-0.2290	-0.0888	-0.1401	2.85	0.0044
2002Q3	-0.1567	-0.1076	-0.0491	-1.61	0.1069
2002Q4	-0.1453	-0.0897	-0.0555	8.36	<.0001
2007Q1	-0.0403	-0.0508	0.0105	-6.97	<.0001
2007Q2	-0.0511	-0.0395	-0.0116	4.40	<.0001
2007Q3	-0.0420	-0.0392	-0.0028	-0.97	0.3315
2007Q4	-0.0589	-0.0280	-0.0310	-3.77	0.0002
2008Q1	-0.0358	-0.0568	0.0210	2.29	0.0223
2008Q2	-0.0497	-0.0448	-0.0049	-4.39	<.0001
2008Q3	-0.0527	-0.0344	-0.0183	-1.01	0.3128
2008Q4	-0.0319	-0.0419	0.0101	0.43	0.6663
2009Q1	-0.0457	-0.0274	-0.0183	-2.35	0.0191
2009Q2	-0.0479	-0.0433	-0.0046	6.05	<.0001

VW	sell	buy	sell-buy	tValue	Probt
1998Q3	-0.0031	-0.0051	0.0020	2.33	0.0200
1998Q4	-0.0075	-0.0041	-0.0034	-2.62	0.0089
1999Q1	-0.0046	-0.0062	0.0016	1.69	0.0912
1999Q2	-0.0070	-0.0024	-0.0046	-4.46	<.0001
1999Q3	-0.0086	-0.0049	-0.0037	-2.41	0.0159
1999Q4	-0.0057	-0.0041	-0.0016	-1.34	0.1792
2000Q1	-0.0038	-0.0083	0.0045	3.75	0.0002
2000Q2	-0.0048	-0.0040	-0.0008	-0.81	0.4178
2000Q3	-0.0134	-0.0024	-0.0110	-6.37	<.0001
2000Q4	-0.0088	-0.0042	-0.0046	-2.36	0.0183
2001Q1	-0.0092	-0.0023	-0.0069	-5.81	<.0001
2001Q2	-0.0042	-0.0048	0.0007	0.59	0.5554
2001Q3	-0.0111	-0.0023	-0.0088	-4.53	<.0001
2001Q4	-0.0032	-0.0060	0.0027	2.17	0.0298
2002Q1	-0.0027	-0.0040	0.0013	1.40	0.1616
2002Q2	-0.0020	-0.0047	0.0027	2.38	0.0176
2002Q3	-0.0040	-0.0040	0.0001	0.07	0.9415
2002Q4	-0.0036	-0.0041	0.0005	0.57	0.5706
2007Q1	-0.0016	-0.0007	-0.0009	-2.06	0.0391
2007Q2	-0.0005	-0.0014	0.0008	2.57	0.0102
2007Q3	-0.0009	-0.0015	0.0006	1.32	0.1870
2007Q4	-0.0017	-0.0005	-0.0011	-2.31	0.0210
2008Q1	-0.0004	-0.0010	0.0006	2.18	0.0291
2008Q2	-0.0007	-0.0006	-0.0001	-0.27	0.7874
2008Q3	-0.0006	-0.0011	0.0005	1.79	0.0739
2008Q4	-0.0008	-0.0014	0.0006	1.17	0.2422
2009Q1	-0.0019	-0.0005	-0.0015	-2.75	0.0061
2009Q2	-0.0005	-0.0011	0.0005	0.73	0.4670

Panel E. Pearson correlation coefficients between stock level liquidity and liquidity beta, liquidity and market beta, and market beta and liquidity beta. I use stocks held by hedge fund managers over 1995-2010. Betas are computed as the coefficient estimates in the regression of stock return in excess of risk-free rate on market excess return and traded liquidity risk using the prior 60 months observations requiring at least 24 months' observations. The stock level liquidity is measured as the monthly average of the daily liquidity measure which is computed as negative signed ratio of absolute value of stock return to dollar volume following Amihud (2002). To measure current month's stock level liquidity I use prior 12 months' stock return and dollar volume to avoid the impact of trading.



Reported are the Pearson correlation coefficients between liquidity and liquidity beta, liquidity and market beta, and liquidity and market betas, and the corresponding p-values. I report only selected quarters to save space. The correlation coefficients are computed over a quarter.

prior	beta_m, beta_l	p-value	Liq, beta_l	p-value	Liq,beta_m	p-value
1998Q3	0.0182	0.5939	-0.0298	0.0093	0.1576	0.0000
1998Q4	0.0920	0.0016	-0.0115	0.0001	0.1526	0.0000
1999Q1	0.0827	0.0006	-0.0581	0.0001	0.1418	0.0000
1999Q2	0.1092	0.0001	-0.0588	0.0000	0.1688	0.0000
1999Q3	0.0947	0.1865	-0.0514	0.0312	0.1365	0.0000
1999Q4	0.0677	0.0000	-0.0150	0.4008	0.1147	0.0000
2000Q1	0.0181	0.0000	-0.0499	0.0000	0.1291	0.0000
2000Q2	-0.0419	0.0000	-0.0961	0.0000	0.1598	0.0000
2000Q3	-0.0479	0.0000	-0.1166	0.0002	0.1557	0.0000
2000Q4	-0.0478	0.0000	-0.1074	0.2758	0.1626	0.0000
2001Q1	-0.0248	0.1857	-0.0649	0.0003	0.1635	0.0000
2001Q2	-0.0404	0.0022	-0.0931	0.0000	0.1468	0.0000
2001Q3	-0.0159	0.0005	-0.0934	0.0000	0.1391	0.0000
2001Q4	0.0486	0.0006	-0.1177	0.0000	0.1496	0.0000
2002Q1	-0.0219	0.0763	-0.1601	0.0000	0.1632	0.0000
2002Q2	-0.0097	0.0042	-0.1286	0.0000	0.1626	0.0000
2002Q3	-0.0303	0.2662	-0.1610	0.0000	0.1625	0.0000
2002Q4	-0.0299	0.0008	-0.1358	0.0000	0.1592	0.0000
2007Q1	-0.1152	0.0000	0.0218	0.3872	0.1241	0.0000
2007Q2	-0.0507	0.0000	-0.0056	0.8673	0.1305	0.0000
2007Q3	-0.0736	0.0000	-0.0052	0.2491	0.1476	0.0000
2007Q4	-0.1622	0.0000	-0.0340	0.2349	0.1515	0.0000
2008Q1	-0.1000	0.0000	0.0057	0.1099	0.1385	0.0000
2008Q2	-0.0809	0.0002	-0.0268	0.6825	0.1597	0.0000
2008Q3	-0.1642	0.0000	-0.0162	0.7056	0.1951	0.0000
2008Q4	-0.3790	0.0000	-0.0338	0.0127	0.1162	0.0000
2009Q1	-0.2471	0.0000	0.0355	0.6730	0.0796	0.0000
2009Q2	-0.2480	0.0000	0.0412	0.0483	0.1056	0.0000

Table 3. Hedge fund managers subject to 13F filings and their stock holdings.

Panel A. Proportion of hedge fund managers subject to 13F filings and the corresponding hedge funds. The affiliation information is from the TASS snapshot as of April 25th, 2012. I obtain the 13F filers' names and their 13F equity holdings information from the Thomson Reuters Institutional (13F) Holdings database. To identify hedge fund managers subject to 13F filings, I first create a list of non-duplicate hedge fund managers' names over the sample period, where hedge fund managers are defined as either a "management company" or "investment company" in a company type field in the TASS database. Also, I make a list of non-duplicate 13F filers' names over the sample period. Then I manually match the hedge fund managers' names to the 13F filers' names. I include all the funds as long as at least one month observation exists for each year. "Final" refers to the managers and the corresponding hedge funds contained in the final sample right before the estimation.

year	Number of HF managers			Number of hedge funds			
	13F HF mgrs	all 13F	% 13F	final	13F match	all TASS	%TASS
1995	21	1,333	1.58%	24	452	1,482	1.62%
1996	48	1,449	3.31%	68	560	1,805	3.77%
1997	66	1,551	4.26%	129	678	2,112	6.11%
1998	94	1,698	5.54%	177	794	2,439	7.26%
1999	117	1,871	6.25%	276	958	2,834	9.74%
2000	143	2,017	7.09%	342	1,162	3,278	10.43%
2001	214	2,156	9.93%	486	1,397	3,938	12.34%
2002	248	2,239	11.08%	585	1,672	4,721	12.39%
2003	264	2,206	11.97%	764	2,015	5,779	13.22%
2004	299	2,313	12.93%	927	2,412	7,109	13.04%
2005	348	2,529	13.76%	1,203	2,780	8,366	14.38%
2006	393	2,704	14.53%	1,388	3,025	9,443	14.70%
2007	451	2,954	15.27%	1,706	3,345	10,454	16.32%
2008	513	3,216	15.95%	1,906	3,427	10,702	17.81%
2009	509	3,248	15.67%	1,717	3,290	10,030	17.12%
2010	462	3,186	14.50%	1,484	3,139	9,275	16.00%

Panel B. Number of stocks held by 13F filers managing hedge funds and the quarterly total equity capitalization for each year.

year	Number of stocks per manager per quarter				Total equity holding per manager per quarter ($mil)				Total equity per qtr
	mean	q1	median	q3	mean	q1	median	q3	%CRSP
1995	426	38	85	240	4,333	171	549	1,560	1.17%
1996	341	35	72	249	4,921	144	437	1,639	2.58%
1997	281	30	73	218	5,036	164	455	1,870	3.32%
1998	265	36	70	227	4,816	146	433	2,266	3.62%
1999	293	37	91	220	6,446	172	463	2,512	5.12%
2000	325	37	91	234	8,116	185	540	3,293	6.00%
2001	332	32	87	233	8,688	110	360	2,374	12.12%
2002	330	35	83	230	8,127	94	331	1,688	14.68%
2003	326	38	86	247	7,579	108	339	1,559	16.01%
2004	326	37	84	266	9,006	138	413	2,005	17.09%
2005	294	32	75	248	8,917	139	452	2,096	17.78%
2006	283	29	68	212	8,682	159	436	1,783	17.83%
2007	287	28	67	216	10,054	163	488	2,062	20.68%
2008	298	23	58	202	8,658	118	415	2,159	22.55%
2009	323	20	60	216	6,583	65	277	1,787	24.23%
2010	354	26	73	265	9,183	127	454	3,008	24.53%

Panel C. Summary statistics of the assets under management (AUM, $ thousands) at the individual fund level. I use monthly non-missing AUM, converted to USD, as of the last day of each corresponding month. “HFs” stands for hedge funds. AUM is obtained from the TASS database, and currency exchange rate information is obtained from WRDS Federal Reserve Bank.

	n	mean	std	q1	med	q3
Final sample	99,150	248,336	768,803	17,143	56,682	181,564
13F HFs	209,265	198,235	632,000	13,162	46,000	150,182
Non-13F HFs	378,689	94,369	267,616	6,580	23,924	77,658

Table 4. Analysis at Portfolio Level I.

I estimate the average fund's alphas by solving equations (6d) to (6f) subject to (6a) to (6c) and (6g) using the GMM method with a Newey-West lag of three. I apply prior quarter-end holdings information to the current quarter information. Because only two funds met my criteria in 1994, the sample for estimation runs from 1995 until 2010. The basic method to form a portfolio is given in the example below; that is, for equally weighted portfolios, the weight is one over the number of managers during the corresponding quarter, while for value-weighted portfolios, it is determined by the prior quarter-end total equity holdings.

Panel A. A simple example of showing how to form a portfolio. Consider two funds A and B and the stock universe consisting of three stocks 1, 2, and 3. For an equally weighted portfolio, I take the average of the positions of the individual managers, with one over the number of managers of the quarter as an equal weight; for a value-weighted portfolio I take the average of the positions of the individual managers with total equity holdings of the prior quarter-end as weights. EWP and VWP stand for equally weighted portfolio and value-weighted portfolio, respectively.

Number of shares held	Fund A	Fund B	Quarter-end price
Stock1	a_1	b_1	p_1
Stock2	a_2	b_2	p_2
Stock3	a_3		p_3
Total holdings	$a_p := a_1 \times p_1 + a_2 \times p_2 + a_3 \times p_3$	$b_p := b_1 \times p_1 + b_2 \times p_2$	

Weight	Fund A	Fund B	EWP	VWP
Stock1	$x_1 := \frac{a_1 \times p_1}{a_p}$	$y_1 := \frac{b_1 \times p_1}{b_p}$	$\frac{x_1 + y_1}{2}$	$\frac{x_1 \times a_p + y_1 \times b_p}{a_p + b_p}$
Stock2	$x_2 := \frac{a_2 \times p_2}{a_p}$	$y_2 := \frac{b_2 \times p_2}{b_p}$	$\frac{x_2 + y_2}{2}$	$\frac{x_2 \times a_p + y_2 \times b_p}{a_p + b_p}$
Stock3	$x_3 := \frac{a_3 \times p_3}{a_p}$	$y_3 := \frac{0 \times p_3}{b_p}$	$\frac{x_3 + 0}{2}$	$\frac{x_3 \times a_p + 0 \times b_p}{a_p + b_p}$
Total	1	1	1	1

Panel B. Estimates of the equally weighted portfolio (average fund) without conditioning information. I estimate the average fund's alphas by solving equations (6d) to (6f) with the market-wide parameter estimates reported in panel B of Table 1. I apply prior quarter-end holdings information to the current quarter information, and the GMM method with a Newey-West lag of three. The estimation period is 1995-2010.

Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0002	0.0032	0.05	0.9595	0.20%
α_L	-0.0006	0.0005	-1.16	0.2489	-0.67%
α_σ	0.0001	0.0007	0.18	0.8598	0.16%
α_S	0.0020	0.0008	2.54	0.012	2.41%
α_{Timing}	-0.0003	0.0038	-0.07	0.9432	-0.32%
α_{Total}	0.0017	0.0038	0.45	0.651	2.08%

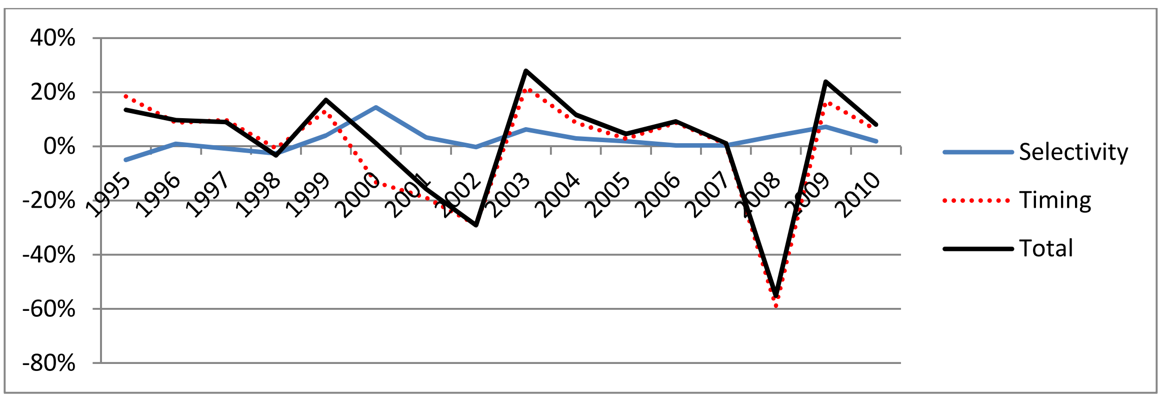
Panel C. Estimates of the equally weighted portfolio with conditioning information. The market-wide parameters are estimated by putting market-wide parameters as linear functions of instruments which are the lagged three-month Treasury bill yield, the lagged dividend price ratio, the lagged term spread, the lagged default return spread, and a dummy variable for the month of January. I apply prior quarter-end holdings information to the current quarter information, and the GMM method with a Newey-West lag of three. The estimation period is 1995-2010.

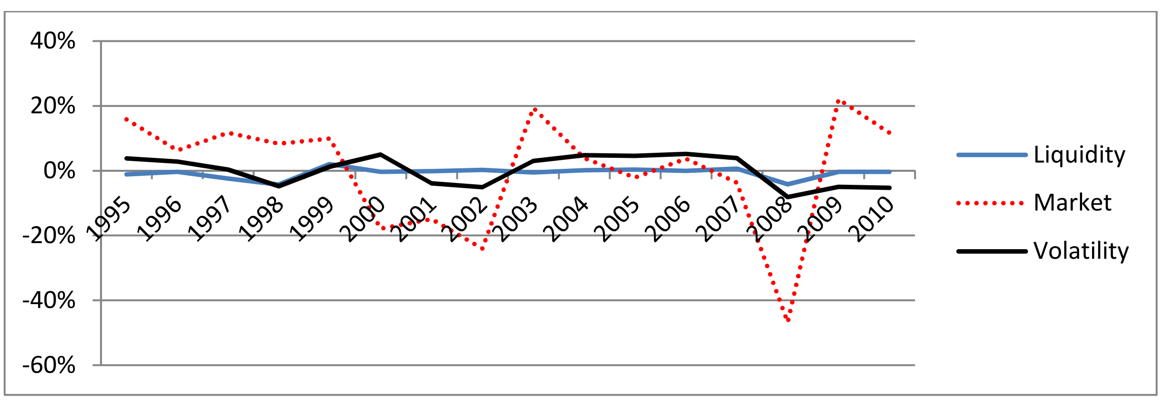
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0002	0.0033	0.06	0.9508	0.25%
α_L	-0.0003	0.0005	-0.61	0.5459	-0.40%
α_σ	0.0003	0.0010	0.26	0.797	0.32%
α_S	0.0020	0.0008	2.37	0.0186	2.39%
α_{Timing}	0.0001	0.0037	0.04	0.9694	0.17%
α_{Total}	0.0021	0.0038	0.56	0.5784	2.56%

Figure 3. Dynamics of Alpha.

The figures depict the dynamics of alphas (percent per year) of the equally weighted portfolio over time. For each year (quarter), I compute each alpha by solving the Euler equations (6d) to (6f) subject to (6a), (6c), and (6g), using 12 months full observations. I apply prior quarter-end holdings information to the current quarter information, and the GMM method with a Newey-West lag of three. The estimation period is 1995-2010.

Panel A. Under unconditional model.

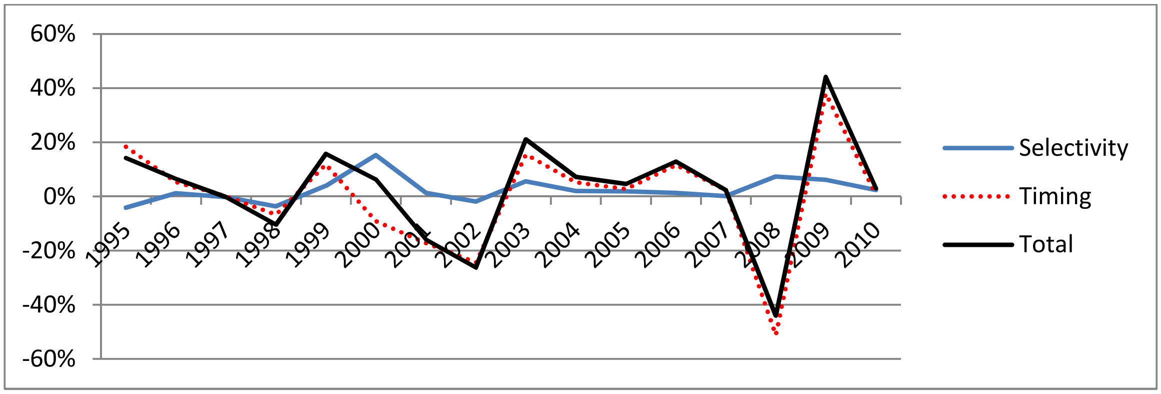


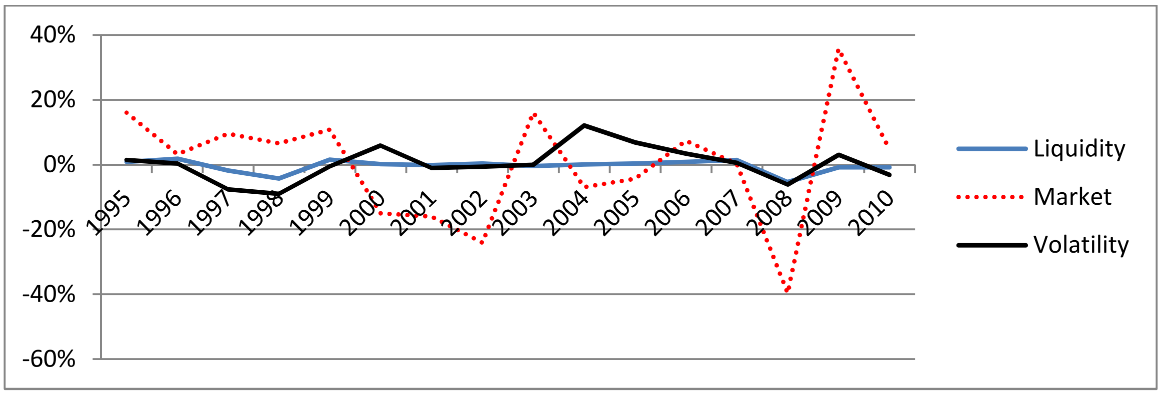


Reported are the monthly alpha estimates of yearly performance, the corresponding standard errors, and the t-statistics.

		1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Selectivity	Estimate	-0.0041	0.0008	-0.0007	-0.0022	0.0033	0.0120	0.0027	-0.0003	0.0052	0.0024	0.0015	0.0003	0.0003	0.0032	0.0059	0.0015
	StdErr	0.0012	0.0017	0.0016	0.0030	0.0036	0.0033	0.0037	0.0034	0.0018	0.0016	0.0014	0.0014	0.0009	0.0038	0.0036	0.0012
	t-value	-3.60	0.49	-0.41	-0.73	0.92	3.60	0.74	-0.08	2.86	1.48	1.10	0.24	0.32	0.85	1.65	1.24
Timing	Estimate	0.0153	0.0072	0.0081	-0.0006	0.0109	-0.0110	-0.0158	-0.0240	0.0181	0.0073	0.0023	0.0073	0.0007	-0.0491	0.0139	0.0051
	StdErr	0.0038	0.0053	0.0073	0.0173	0.0088	0.0126	0.0111	0.0113	0.0071	0.0068	0.0049	0.0065	0.0059	0.0241	0.0174	0.0140
	t-value	4.01	1.36	1.11	-0.04	1.23	-0.88	-1.42	-2.13	2.54	1.08	0.48	1.12	0.11	-2.03	0.80	0.36
Total	Estimate	0.0112	0.0081	0.0074	-0.0028	0.0142	0.0010	-0.0131	-0.0242	0.0232	0.0097	0.0039	0.0076	0.0009	-0.0459	0.0198	0.0066
	StdErr	0.0045	0.0052	0.0075	0.0177	0.0096	0.0097	0.0130	0.0140	0.0077	0.0081	0.0059	0.0072	0.0052	0.0262	0.0157	0.0131
	t-value	2.48	1.55	0.98	-0.16	1.49	0.10	-1.00	-1.72	3.02	1.20	0.65	1.06	0.18	-1.75	1.26	0.50
Liquidity	Estimate	-0.0010	-0.0003	-0.0020	-0.0036	0.0017	-0.0003	-0.0002	0.0002	-0.0005	0.0001	0.0003	0.0000	0.0005	-0.0035	-0.0003	-0.0003
	StdErr	0.0013	0.0018	0.0022	0.0026	0.0012	0.0042	0.0004	0.0001	0.0002	0.0001	0.0001	0.0009	0.0012	0.0033	0.0013	0.0003
	t-value	-0.73	-0.16	-0.88	-1.39	1.36	-0.06	-0.40	1.41	-2.73	1.73	2.24	-0.02	0.44	-1.04	-0.24	-0.88
Market	Estimate	0.0132	0.0052	0.0097	0.0069	0.0082	-0.0149	-0.0124	-0.0200	0.0161	0.0032	-0.0017	0.0030	-0.0031	-0.0389	0.0183	0.0097
	StdErr	0.0026	0.0055	0.0066	0.0139	0.0087	0.0085	0.0103	0.0112	0.0077	0.0069	0.0049	0.0063	0.0051	0.0172	0.0157	0.0138
	t-value	4.97	0.95	1.48	0.50	0.95	-1.76	-1.20	-1.78	2.09	0.46	-0.35	0.48	-0.60	-2.26	1.17	0.71
Volatility	Estimate	0.0031	0.0023	0.0003	-0.0040	0.0010	0.0041	-0.0032	-0.0042	0.0025	0.0040	0.0038	0.0043	0.0032	-0.0067	-0.0041	-0.0044
	StdErr	0.0002	0.0010	0.0010	0.0033	0.0011	0.0020	0.0015	0.0033	0.0006	0.0003	0.0002	0.0002	0.0004	0.0056	0.0024	0.0019
	t-value	18.65	2.36	0.33	-1.20	0.95	2.03	-2.13	-1.28	3.98	13.17	20.32	19.89	8.43	-1.22	-1.70	-2.24

Panel B. Under conditional model.





Reported are the monthly alpha estimates of yearly performance, the corresponding standard errors and t-statistics.

		1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Selectivity	Estimate	-0.0035	0.0009	-0.0002	-0.0031	0.0032	0.0127	0.0011	-0.0016	0.0046	0.0017	0.0015	0.0011	0.0001	0.0061	0.0051	0.0020
	StdErr	0.0009	0.0021	0.0016	0.0033	0.0040	0.0031	0.0036	0.0042	0.0015	0.0017	0.0014	0.0018	0.0009	0.0019	0.0034	0.0015
	t-value	-3.79	0.45	-0.15	-0.93	0.81	4.06	0.30	-0.39	2.97	0.96	1.10	0.59	0.13	3.16	1.52	1.33
Timing	Estimate	0.0153	0.0045	0.0000	-0.0056	0.0098	-0.0076	-0.0143	-0.0202	0.0129	0.0043	0.0023	0.0096	0.0019	-0.0426	0.0315	0.0005
	StdErr	0.0052	0.0079	0.0082	0.0212	0.0088	0.0092	0.0101	0.0151	0.0059	0.0070	0.0050	0.0079	0.0055	0.0202	0.0158	0.0152
	t-value	2.92	0.57	0.00	-0.26	1.11	-0.82	-1.42	-1.34	2.18	0.62	0.46	1.21	0.34	-2.11	1.99	0.03
Total	Estimate	0.0118	0.0054	-0.0002	-0.0086	0.0130	0.0052	-0.0132	-0.0219	0.0175	0.0060	0.0038	0.0107	0.0020	-0.0365	0.0366	0.0025
	StdErr	0.0056	0.0066	0.0077	0.0221	0.0088	0.0074	0.0123	0.0184	0.0063	0.0084	0.0061	0.0093	0.0048	0.0203	0.0185	0.0141
	t-value	2.11	0.82	-0.03	-0.39	1.49	0.70	-1.07	-1.19	2.77	0.71	0.63	1.16	0.41	-1.80	1.98	0.18
Liquidity	Estimate	0.0007	0.0016	-0.0015	-0.0035	0.0013	0.0001	-0.0002	0.0003	-0.0003	0.0001	0.0003	0.0007	0.0012	-0.0045	-0.0007	-0.0007
	StdErr	0.0016	0.0024	0.0027	0.0026	0.0013	0.0044	0.0004	0.0002	0.0002	0.0001	0.0001	0.0009	0.0013	0.0038	0.0014	0.0003
	t-value	0.43	0.65	-0.56	-1.37	0.98	0.02	-0.45	1.30	-1.87	0.81	2.32	0.78	0.91	-1.19	-0.49	-2.28
Market	Estimate	0.0133	0.0026	0.0079	0.0055	0.0090	-0.0125	-0.0133	-0.0200	0.0133	-0.0057	-0.0037	0.0061	0.0002	-0.0330	0.0297	0.0039
	StdErr	0.0038	0.0075	0.0080	0.0150	0.0094	0.0077	0.0104	0.0122	0.0075	0.0081	0.0058	0.0071	0.0057	0.0169	0.0175	0.0137
	t-value	3.53	0.35	0.99	0.37	0.96	-1.62	-1.27	-1.63	1.77	-0.71	-0.63	0.85	0.04	-1.95	1.70	0.28
Volatility	Estimate	0.0012	0.0003	-0.0064	-0.0075	-0.0005	0.0049	-0.0009	-0.0005	-0.0001	0.0100	0.0057	0.0029	0.0005	-0.0051	0.0025	-0.0027
	StdErr	0.0022	0.0052	0.0034	0.0067	0.0020	0.0037	0.0020	0.0033	0.0030	0.0015	0.0012	0.0019	0.0017	0.0022	0.0071	0.0024
	t-value	0.56	0.05	-1.90	-1.12	-0.25	1.31	-0.45	-0.15	-0.02	6.80	4.85	1.48	0.27	-2.30	0.36	-1.12

Table 5. Analysis at Portfolio Level II.

I estimate the alphas for the equally weighted portfolio for each sub-period, which is split according to widely accepted structural break points. I apply prior quarter-end holdings information to the current quarter information. The estimation method is GMM with a Newey-West lag of three. Sub-periods are the period up to LTCM collapse and just before the tech bubble (January 1995 to September 1998), the tech bubble (October 1998 to March 2000), the NASDAQ crash, the accounting scandal and September 11 attacks (April 2000 to October 2002), the period leading up to the mortgage crisis (November 2002 to June 2007), the recent financial crisis (July 2007 to December 2008), and the remaining period (January 2009 to December 2010).

199501-199809					
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0064	0.0042	1.54	0.1307	7.76%
α_L	-0.0021	0.0011	-1.88	0.0668	-2.47%
α_σ	0.0007	0.0012	0.57	0.5745	0.82%
α_S	-0.0010	0.0009	-1.11	0.2712	-1.24%
α_{Timing}	0.0051	0.0055	0.92	0.3608	6.11%
α_{Total}	0.0040	0.0057	0.71	0.4786	4.86%

199810-200003					
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0134	0.0070	1.91	0.0728	16.07%
α_L	0.0033	0.0024	1.41	0.1758	4.00%
α_σ	0.0019	0.0016	1.21	0.2429	2.27%
α_S	0.0009	0.0034	0.26	0.8004	1.03%
α_{Timing}	0.0186	0.0081	2.3	0.0347	22.34%
α_{Total}	0.0194	0.0070	2.77	0.0132	23.38%

200004-200210					
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	-0.0185	0.0062	-3	0.0055	-22.31%
α_L	-0.0010	0.0011	-0.92	0.3649	-1.24%
α_σ	-0.0020	0.0016	-1.2	0.2406	-2.35%
α_S	0.0049	0.0032	1.54	0.1340	5.87%
α_{Timing}	-0.0215	0.0072	-2.97	0.0058	-25.89%
α_{Total}	-0.0166	0.0083	-2	0.0547	-20.02%

200211-200706					
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0048	0.0033	1.44	0.1555	5.74%
α_L	0.0002	0.0003	0.81	0.4214	0.30%
α_σ	0.0033	0.0004	9.25	<.0001	4.00%
α_S	0.0023	0.0009	2.63	0.0111	2.78%
α_{Timing}	0.0083	0.0032	2.59	0.0122	10.04%
α_{Total}	0.0107	0.0037	2.92	0.0051	12.81%

200707-200812					
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	-0.0293	0.0132	-2.22	0.0407	-35.27%
α_L	-0.0028	0.0023	-1.21	0.2412	-3.38%
α_σ	-0.0035	0.0042	-0.85	0.4092	-4.26%
α_S	0.0025	0.0026	0.95	0.3554	2.99%
α_{Timing}	-0.0357	0.0185	-1.93	0.0701	-42.91%
α_{Total}	-0.0332	0.0193	-1.72	0.1038	-39.92%

200901-201012					
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0140	0.0104	1.34	0.1922	16.86%
α_L	-0.0003	0.0006	-0.45	0.6604	-0.34%
α_σ	-0.0042	0.0016	-2.64	0.0146	-5.10%
α_S	0.0037	0.0020	1.9	0.0699	4.48%
α_{Timing}	0.0095	0.0112	0.85	0.4037	11.42%
α_{Total}	0.0132	0.0105	1.26	0.2213	15.90%

Table 6. Capital Constraints.

Using the TASS snapshot as of April 25, 2012, managers are ranked according to the length of the lock-up period, redemption-notice periods, and average leverage (debt over AUM). Because a manager is usually matched to multiple funds, I rank each manager according to the average of each variable across funds. Then I form a portfolio of going long the funds with the strongest share restrictions or highest average leverage, and short those with the weakest share restrictions or lowest average leverage. Depicted are the alpha differences (percent per year) of the top and bottom portfolios for each capital constraint. I apply prior quarter-end holdings information to the current quarter information, and the GMM method with a Newey-West lag of three. The estimation period is 1995-2010.

Panel A. Lock-up period. I split the sample into two sub-samples. The mean lock-up period for the top portfolio (343 managers) is 9.34 months and that for the bottom (298 managers) is 0.

Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0001	0.0002	0.38	0.7041	0.09%
α_L	-0.0001	0.0002	-0.22	0.8259	-0.06%
α_σ	0.0001	0.0001	1.01	0.312	0.15%
α_S	0.0008	0.0005	1.70	0.0909	0.93%
α_{Timing}	0.0001	0.0003	0.44	0.6605	0.18%
α_{Total}	0.0009	0.0006	1.56	0.1194	1.11%

Panel B. Redemption-notice period. I break the sample down into three sub-samples. The mean redemption-notice period for the top tercile portfolio (176 managers) is 68.17 months and that for the bottom (178 managers) is 11.76 months.

Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0005	0.0003	1.60	0.1106	0.64%
α_L	0.0001	0.0003	0.36	0.7173	0.11%
α_σ	0.0001	0.0001	1.70	0.0909	0.18%
α_S	0.0011	0.0006	1.93	0.0548	1.36%
α_{Timing}	0.0008	0.0004	1.90	0.0597	0.93%
α_{Total}	0.0019	0.0007	2.90	0.0042	2.29%

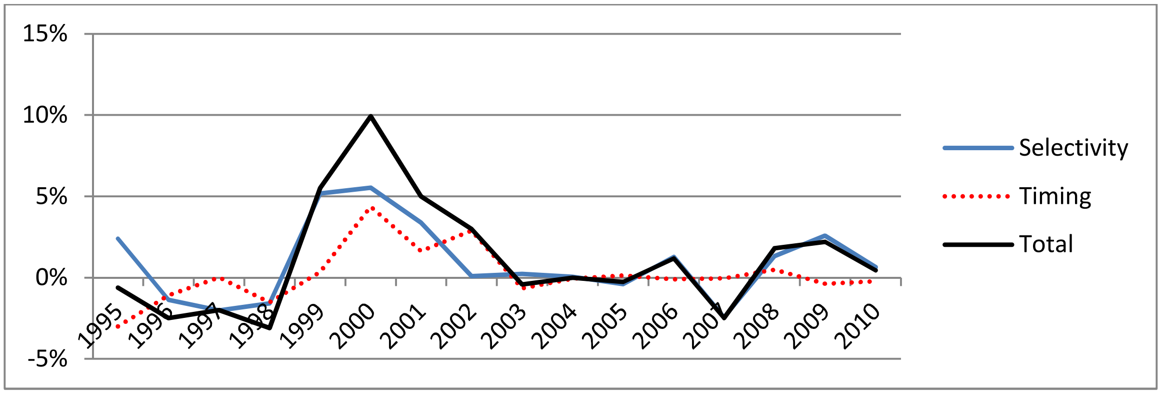
Panel C. Average leverage. I split the sample into two sub-samples because more than half of the sample (349 managers) reports average leverage of 0%. The mean leverage for non-zero average leverage managers (292 managers) is 90.73%.

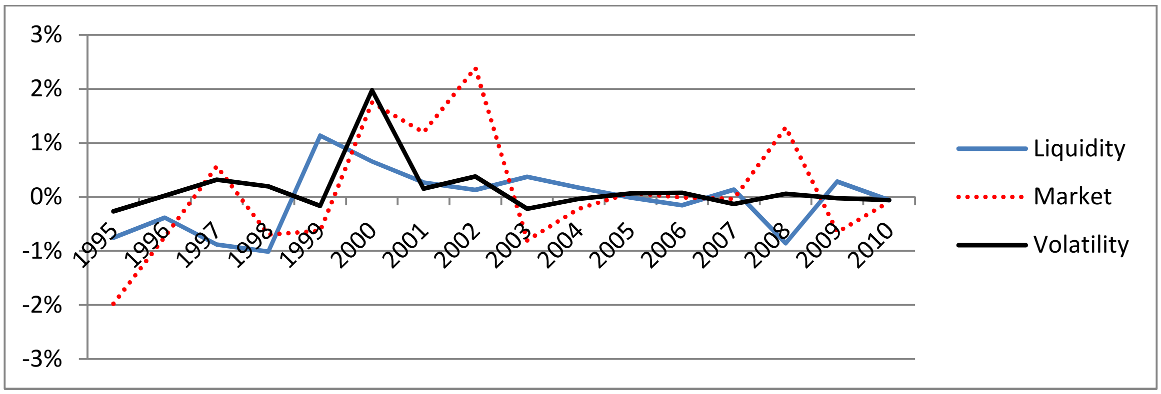
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	0.0000	0.0002	0.02	0.9876	0.00%
α_L	0.0002	0.0002	1.19	0.2345	0.22%
α_σ	0.0000	0.0000	0.78	0.4341	0.04%
α_S	0.0004	0.0004	0.9	0.3709	0.42%
α_{Timing}	0.0002	0.0003	0.75	0.4548	0.26%
α_{Total}	0.0006	0.0005	1.22	0.2223	0.69%

Figure 4. Capital Constraints.

Using the TASS snapshot as of April 25, 2012, managers are ranked according to the length of the lock-up period and redemption-notice period, and average leverage (debt over AUM). Because a manager is usually matched to multiple funds, I rank each manager according to the average of each variable across its funds. Then I form a portfolio of going long the funds with the strongest share restrictions or highest average leverage, and short those with the weakest share restrictions or lowest average leverage. Then I estimate the portfolio alphas by solving equations (6d) to (6f) subject to (6a) to (6c) and (6g) using the GMM method with a Newey-West lag of three, and full 12 months of observations. I apply prior quarter-end holdings information to the current quarter information. Depicted are the yearly alpha differences (percent per year) between the top and bottom portfolios for each capital constraint.

Panel A. Lock-up period. I split the sample into two sub-samples. The mean lock-up period for the top portfolio (343 managers) is 9.34 months and that for the bottom (298 managers) is 0.





Reported are the monthly alpha estimates of yearly performance, the corresponding standard errors and t-statistics.

		1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Selectivity	Estimate	0.0020	-0.0011	-0.0017	-0.0013	0.0043	0.0046	0.0028	0.0001	0.0002	0.0001	-0.0003	0.0011	-0.0020	0.0011	0.0021	0.0005
	StdErr	0.0013	0.0029	0.0018	0.0016	0.0019	0.0019	0.0011	0.0010	0.0012	0.0005	0.0003	0.0009	0.0009	0.0012	0.0012	0.0008
	t-value	1.53	-0.39	-0.93	-0.81	2.30	2.41	2.63	0.08	0.17	0.10	-1.21	1.18	-2.16	0.90	1.79	0.64
Timing	Estimate	-0.0025	-0.0009	0.0000	-0.0013	0.0003	0.0036	0.0013	0.0024	-0.0005	-0.0001	0.0001	-0.0001	0.0000	0.0004	-0.0003	-0.0002
	StdErr	0.0006	0.0014	0.0012	0.0013	0.0006	0.0032	0.0004	0.0011	0.0007	0.0002	0.0000	0.0002	0.0004	0.0013	0.0003	0.0004
	t-value	-4.39	-0.68	0.01	-0.94	0.46	1.12	3.20	2.11	-0.79	-0.28	2.38	-0.37	-0.08	0.30	-1.00	-0.47
Total	Estimate	-0.0005	-0.0021	-0.0017	-0.0026	0.0046	0.0082	0.0042	0.0025	-0.0003	0.0000	-0.0002	0.0010	-0.0021	0.0015	0.0018	0.0004
	StdErr	0.0018	0.0029	0.0022	0.0013	0.0017	0.0042	0.0012	0.0011	0.0007	0.0006	0.0003	0.0010	0.0013	0.0006	0.0011	0.0009
	t-value	-0.29	-0.72	-0.75	-2.00	2.72	1.98	3.54	2.30	-0.50	-0.01	-0.80	0.94	-1.63	2.52	1.61	0.40
Liquidity	Estimate	-0.0006	-0.0003	-0.0007	-0.0008	0.0009	0.0005	0.0002	0.0001	0.0003	0.0001	0.0000	-0.0001	0.0001	-0.0007	0.0002	-0.0001
	StdErr	0.0002	0.0009	0.0011	0.0009	0.0008	0.0026	0.0004	0.0001	0.0001	0.0001	0.0000	0.0001	0.0003	0.0011	0.0005	0.0001
	t-value	-2.64	-0.36	-0.66	-0.97	1.21	0.21	0.61	0.74	3.54	1.90	-0.83	-1.04	0.37	-0.68	0.43	-0.43
Market	Estimate	-0.0016	-0.0006	0.0005	-0.0006	-0.0005	0.0014	0.0010	0.0020	-0.0007	-0.0002	0.0001	0.0000	0.0000	0.0011	-0.0005	-0.0001
	StdErr	0.0004	0.0007	0.0006	0.0010	0.0006	0.0010	0.0005	0.0011	0.0007	0.0002	0.0001	0.0001	0.0001	0.0006	0.0005	0.0003
	t-value	-4.56	-0.92	0.83	-0.59	-0.88	1.50	2.14	1.85	-0.94	-1.07	1.30	-0.08	-0.23	1.80	-1.08	-0.24
Volatility	Estimate	-0.0002	0.0000	0.0003	0.0002	-0.0001	0.0016	0.0001	0.0003	-0.0002	0.0000	0.0001	0.0001	-0.0001	0.0000	0.0000	-0.0001
	StdErr	0.0001	0.0002	0.0001	0.0001	0.0001	0.0017	0.0001	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0001	0.0000
	t-value	-3.41	0.11	2.14	1.13	-1.14	0.95	1.78	1.40	-3.73	-0.66	2.54	1.61	-2.86	0.22	-0.22	-1.56

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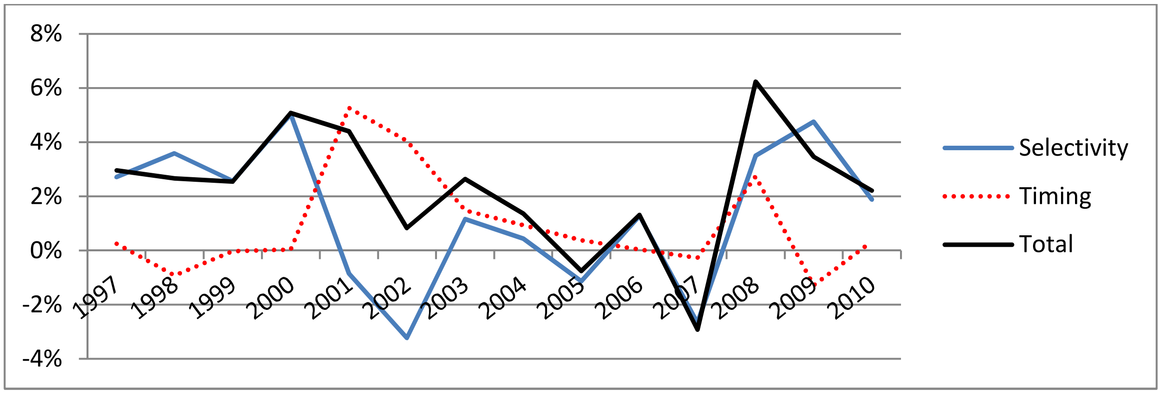
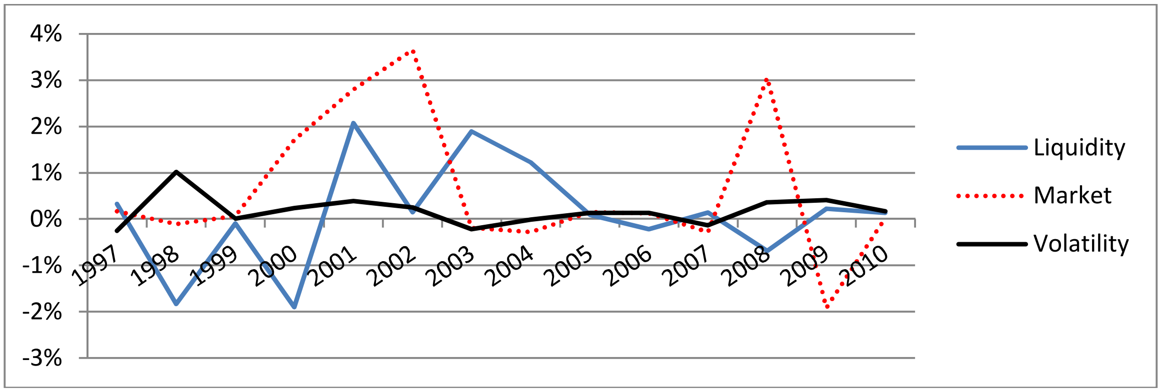
Panel B. Redemption-notice period. I break the sample down into three sub-samples. The mean redemption-notice period for the top tercile portfolio (174 managers) is 68 months and that for the bottom (172 managers) is 12 months.

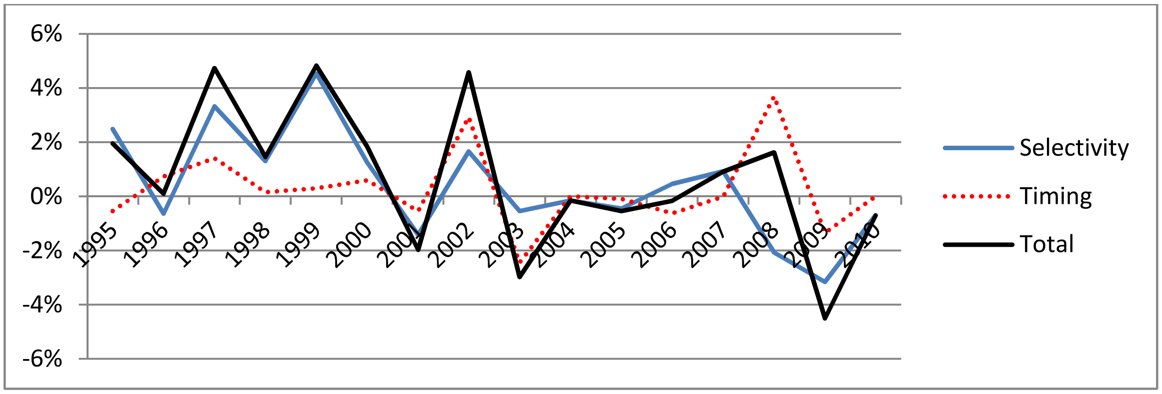


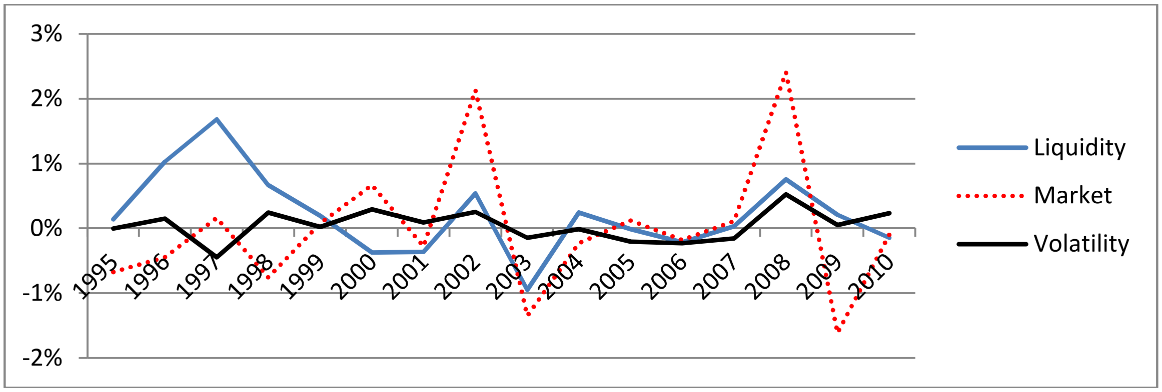


Reported are the monthly alpha estimates of yearly performance, the corresponding standard errors and t-statistics.

		1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Selectivity	Estimate	0.0023	0.0030	0.0021	0.0042	-0.0007	-0.0027	0.0010	0.0004	-0.0009	0.0011	-0.0022	0.0029	0.0039	0.0016
	StdErr	0.0013	0.0012	0.0022	0.0040	0.0021	0.0023	0.0012	0.0017	0.0007	0.0015	0.0011	0.0012	0.0029	0.0015
	t-value	1.77	2.43	0.95	1.04	-0.34	-1.15	0.78	0.22	-1.45	0.73	-2.06	2.49	1.37	1.08
Timing	Estimate	0.0002	-0.0008	0.0000	0.0000	0.0044	0.0034	0.0012	0.0008	0.0003	0.0000	-0.0002	0.0023	-0.0011	0.0003
	StdErr	0.0013	0.0032	0.0005	0.0012	0.0012	0.0014	0.0005	0.0006	0.0004	0.0003	0.0004	0.0020	0.0011	0.0004
	t-value	0.16	-0.24	-0.03	0.03	3.60	2.47	2.36	1.20	0.77	0.10	-0.54	1.14	-0.97	0.70
Total	Estimate	0.0025	0.0022	0.0021	0.0042	0.0037	0.0007	0.0022	0.0011	-0.0006	0.0011	-0.0024	0.0052	0.0029	0.0018
	StdErr	0.0020	0.0024	0.0025	0.0048	0.0022	0.0025	0.0013	0.0018	0.0008	0.0015	0.0014	0.0018	0.0031	0.0016
	t-value	1.21	0.94	0.86	0.88	1.65	0.27	1.66	0.62	-0.80	0.71	-1.78	2.95	0.92	1.14
Liquidity	Estimate	0.0003	-0.0015	-0.0001	-0.0016	0.0017	0.0001	0.0016	0.0010	0.0001	-0.0002	0.0001	-0.0006	0.0002	0.0001
	StdErr	0.0013	0.0008	0.0001	0.0019	0.0014	0.0007	0.0006	0.0004	0.0002	0.0002	0.0002	0.0003	0.0005	0.0001
	t-value	0.21	-1.99	-0.83	-0.82	1.26	0.18	2.84	2.26	0.51	-1.08	0.48	-2.08	0.39	1.67
Market	Estimate	0.0001	-0.0001	0.0001	0.0014	0.0023	0.0030	-0.0002	-0.0002	0.0001	0.0001	-0.0002	0.0025	-0.0016	0.0000
	StdErr	0.0001	0.0026	0.0005	0.0012	0.0012	0.0011	0.0006	0.0002	0.0003	0.0003	0.0002	0.0016	0.0008	0.0004
	t-value	1.02	-0.03	0.12	1.22	1.99	2.75	-0.26	-1.11	0.45	0.35	-0.96	1.59	-2.12	0.06
Volatility	Estimate	-0.0002	0.0008	0.0000	0.0002	0.0003	0.0002	-0.0002	0.0000	0.0001	0.0001	-0.0001	0.0003	0.0003	0.0001
	StdErr	0.0001	0.0007	0.0001	0.0006	0.0003	0.0003	0.0001	0.0001	0.0001	0.0000	0.0000	0.0004	0.0002	0.0000
	t-value	-1.89	1.28	0.14	0.31	1.30	0.77	-3.10	-0.16	1.68	2.33	-4.16	0.70	1.48	3.96

Panel C. Average leverage. I split the sample into two sub-samples because more than half of the sample (349 managers) reports average leverage of 0%. The average leverage for non-zero average leverage managers (292 managers) is 90.73%.





Reported are the monthly alpha estimates of yearly performance, the corresponding standard errors and t-statistics.

		1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Selectivity	Estimate	0.0021	-0.0005	0.0028	0.0011	0.0038	0.0010	-0.0012	0.0014	-0.0005	-0.0001	-0.0004	0.0004	0.0008	-0.0017	-0.0026	-0.0006
	StdErr	0.0023	0.0028	0.0012	0.0014	0.0010	0.0015	0.0015	0.0014	0.0012	0.0008	0.0004	0.0005	0.0004	0.0013	0.0014	0.0004
	t-value	0.89	-0.19	2.23	0.75	3.61	0.71	-0.80	0.97	-0.40	-0.17	-0.83	0.74	1.83	-1.35	-1.90	-1.33
Timing	Estimate	-0.0005	0.0006	0.0012	0.0001	0.0002	0.0005	-0.0005	0.0024	-0.0020	0.0000	-0.0001	-0.0005	0.0000	0.0031	-0.0011	0.0000
	StdErr	0.0007	0.0008	0.0014	0.0009	0.0006	0.0015	0.0010	0.0011	0.0014	0.0001	0.0002	0.0003	0.0002	0.0018	0.0007	0.0007
	t-value	-0.66	0.75	0.82	0.15	0.44	0.33	-0.45	2.22	-1.46	0.02	-0.46	-1.82	-0.04	1.74	-1.64	0.00
Total	Estimate	0.0016	0.0001	0.0039	0.0012	0.0040	0.0015	-0.0016	0.0038	-0.0025	-0.0001	-0.0005	-0.0001	0.0008	0.0014	-0.0037	-0.0006
	StdErr	0.0029	0.0023	0.0018	0.0013	0.0009	0.0020	0.0018	0.0020	0.0008	0.0007	0.0004	0.0007	0.0004	0.0018	0.0016	0.0009
	t-value	0.57	0.03	2.23	0.91	4.30	0.76	-0.91	1.94	-3.20	-0.18	-1.11	-0.21	1.99	0.73	-2.38	-0.69
Liquidity	Estimate	0.0001	0.0009	0.0014	0.0006	0.0002	-0.0003	-0.0003	0.0005	-0.0008	0.0002	0.0000	-0.0002	0.0000	0.0006	0.0002	-0.0001
	StdErr	0.0003	0.0003	0.0014	0.0004	0.0002	0.0013	0.0004	0.0005	0.0004	0.0002	0.0001	0.0001	0.0000	0.0004	0.0005	0.0001
	t-value	0.34	2.76	1.03	1.56	0.85	-0.24	-0.81	0.92	-2.20	1.21	-0.23	-1.93	0.81	1.73	0.34	-2.06
Market	Estimate	-0.0006	-0.0004	0.0001	-0.0006	0.0001	0.0006	-0.0002	0.0018	-0.0011	-0.0002	0.0001	-0.0002	0.0001	0.0020	-0.0013	-0.0001
	StdErr	0.0004	0.0007	0.0005	0.0007	0.0004	0.0005	0.0006	0.0012	0.0011	0.0001	0.0002	0.0003	0.0002	0.0013	0.0012	0.0007
	t-value	-1.25	-0.53	0.29	-0.92	0.15	1.06	-0.39	1.45	-1.02	-2.11	0.48	-0.58	0.59	1.57	-1.16	-0.11
Volatility	Estimate	0.0000	0.0001	-0.0004	0.0002	0.0000	0.0002	0.0001	0.0002	-0.0001	0.0000	-0.0002	-0.0002	-0.0001	0.0004	0.0000	0.0002
	StdErr	0.0001	0.0001	0.0001	0.0002	0.0001	0.0003	0.0001	0.0002	0.0001	0.0000	0.0000	0.0001	0.0000	0.0004	0.0001	0.0001
	t-value	-0.04	0.85	-4.90	1.20	0.35	0.83	0.54	1.11	-1.26	-0.28	-5.58	-2.41	-3.78	1.19	0.51	2.05

Table 7. Non-Long Equity Positions

Panel A. Returns-Based Measure. I use those hedge funds whose managers are matched to the managers in the final sample. I control for backfill bias by choosing the return observations after a fund was added to the TASS database. Then I form an equally weighted portfolio by computing the average return across the funds for each month over the January 1995 to December 2010. I obtain the (timing) performance estimates following Treynor and Mazuy (1966) and Cao et al. (2012). That is, the market timing, liquidity timing, and volatility timing are measured as the coefficient estimates of β, γ, and θ, respectively, in the following regression:

$$eret_{p,t} = \alpha + \beta MKTRF_t^2 + \gamma MKTRF_t \times LIQ_t^d + \theta MKTRF_t \times VIX_t^d + FH7\ factors,$$

where $eret_{p,t}$ is the portfolio return in excess of risk-free rate at month t, $MKTRF_t$ is the market excess return in month t, LIQ_t^d the demeaned traded Amihud liquidity factor, VIX_t^d the demeaned VIX, and $FH7\ factors$ the Fung and Hsieh seven factors, which include trend following factors (bond (PTFSBD), currency (PTFSFX), and commodity (PTFSCOM)), equity-oriented risk factors (equity market (MKTRF), size spread factor (SMB)), and bond-oriented risk factors (bond market (YLDCHG), credit spread factor (BAAMTSY)). VIX (Chicago Board Options Exchange (CBOE) Market Volatility Index) data are obtained from CBOE website.

Parameter	Estimate	StdErr	DF	t-value	Probt
Intercept	0.0033	0.0012	191	2.83	0.0051
MKTRF	0.2768	0.0223	191	12.44	<.0001
$MKTRF_T^2$	-0.0638	0.4040	191	-0.16	0.8747
$MKTRF_t \times LIQ_t^d$	-0.1203	0.3510	191	-0.34	0.7322
$MKTRF_t \times VIX_t^d$	0.0161	0.1921	191	0.08	0.9331
SMB	0.1271	0.0337	191	3.77	0.0002
YLDCHG	-0.0166	0.0038	191	-4.31	<.0001
BAAMTSY	-0.0288	0.0078	191	-3.70	0.0003
PTFSBD	-0.0088	0.0062	191	-1.42	0.1560
PTFSFX	0.0119	0.0069	191	1.73	0.0853
PTFSCOM	0.0098	0.0086	191	1.14	0.2567

Panel B. Derivatives Users vs. Non-Users. I use the average of the "Derivatives" indicator across funds for each manager. The indicator is from the TASS snapshot as of April 25, 2012. I split the sample into two sub-samples because more than half are non-users (173 managers are classified as users and 468 as non-users). I form an equally weighed portfolio of going long positions of the derivative users and short those of the non-users. Then I estimate the individual funds' alphas by solving equations (6d) to (6f) subject to (6a) to (6c) and (6g) using the GMM method with a Newey-West lag of three and full 12 months of observation. I apply prior quarter-end holdings information to the current quarter information.

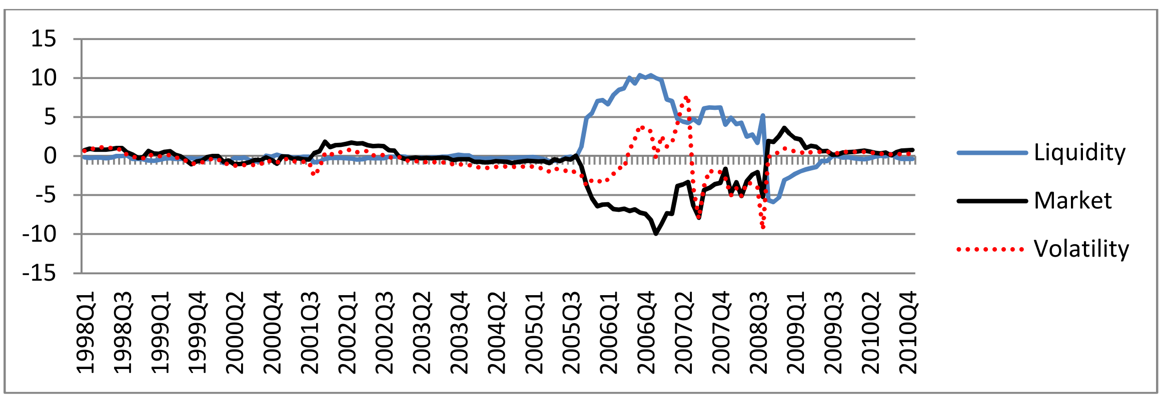
Parameter	Estimate	StdErr	t-value	Probt	p.a.
α_M	-0.0001	0.0002	-0.53	0.5994	-0.11%
α_L	-0.0002	0.0002	-0.81	0.4189	-0.23%
α_σ	-0.0001	0.0001	-1.64	0.1028	-0.14%
α_S	0.0001	0.0004	0.3	0.7644	0.13%
α_{Timing}	-0.0004	0.0003	-1.26	0.2109	-0.47%
α_{Total}	-0.0003	0.0004	-0.74	0.4608	-0.34%

Figure 5. Non-Long Equity Positions.

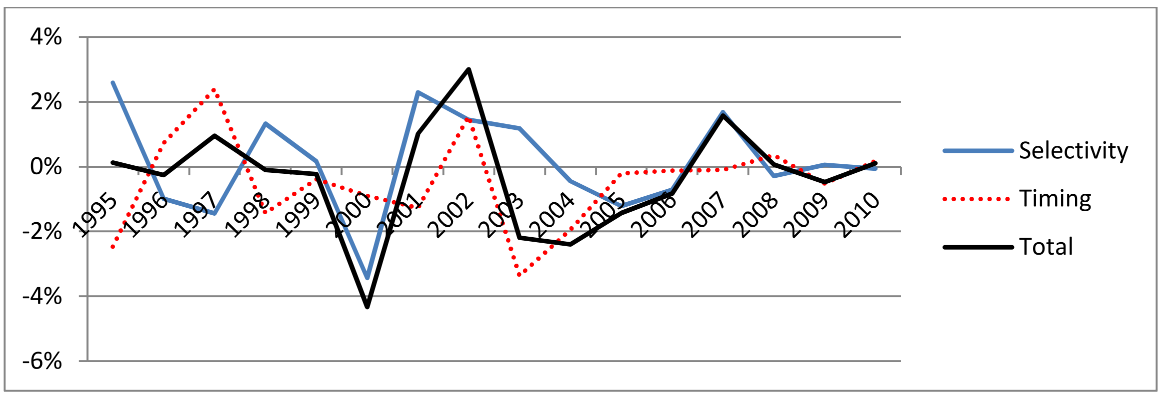
Panel A. Returns-based measure. I use those hedge funds whose managers are matched to the managers in the final sample. I control for backfill bias by choosing the return observations after a fund was added to the TASS database. Then I form an equally weighted portfolio by computing the average return across the funds for each month over the January 1995 to December 2010. I obtain the (timing) performance estimates following Treynor and Mazuy (1966) and Cao et al. (2012). That is, the market timing, liquidity timing, and volatility timing are measured as the coefficient estimates, β, γ, and θ, respectively, in the following regression:

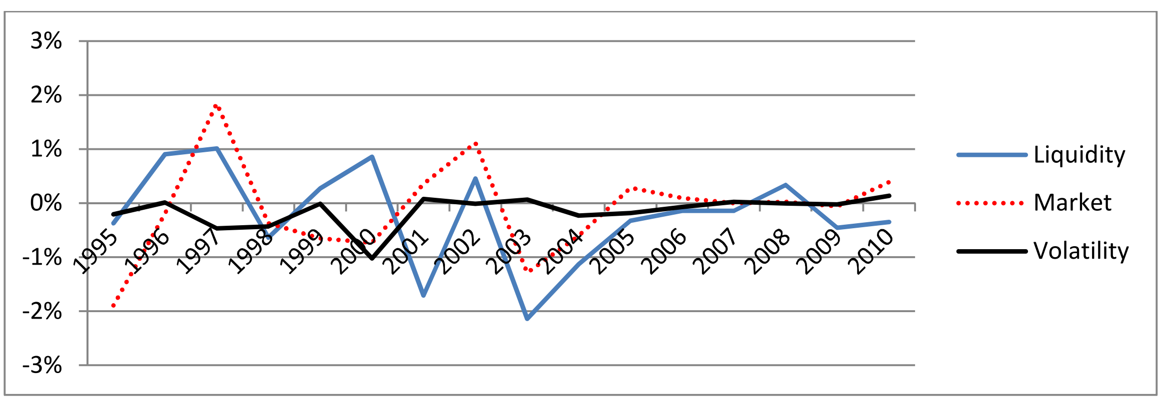
$$eret_{p,t} = \alpha + \beta MKTRF_t^2 + \gamma MKTRF_t \times LIQ_t^d + \theta MKTRF_t \times VIX_t^d + FH7\ factors,$$

where $eret_{p,t}$ is the portfolio return in excess of risk-free rate at month t, $MKTRF_t$ is the market excess return in month t, LIQ_t^d the demeaned traded Amihud liquidity factor, VIX_t^d the demeaned VIX, and $FH7\ factors$ the Fung and Hsieh seven factors, which include trend following factors (bond (PTFSBD), currency (PTFSFX), and commodity (PTFSCOM)), equity-oriented risk factors (equity market (MKTRF), size spread factor (SMB)), and bond-oriented risk factors (bond market (YLDCHG), credit spread factor (BAAMTSY)). VIX (Chicago Board Options Exchange Market Volatility Index) data are obtained from CBOE website.



Panel B. Derivaties Users and Non-Users. I use the average of the “Derivatives” indicator across funds for each manager. The indicator is from the TASS snapshot as of April 25, 2012. I split the sample into two sub-samples because more than half are non-users (173 managers are classified as users and 468 as non-users). I form an equally weighed portfolio of going long the derivative users and short the non-users. Then I estimate the individual funds’ alphas by solving equations (6d) to (6f) subject to (6a) to (6c) and (6g) using the GMM method with a Newey-West lag of three and full 12 months of observation. I apply prior quarter-end holdings information to the current quarter information.



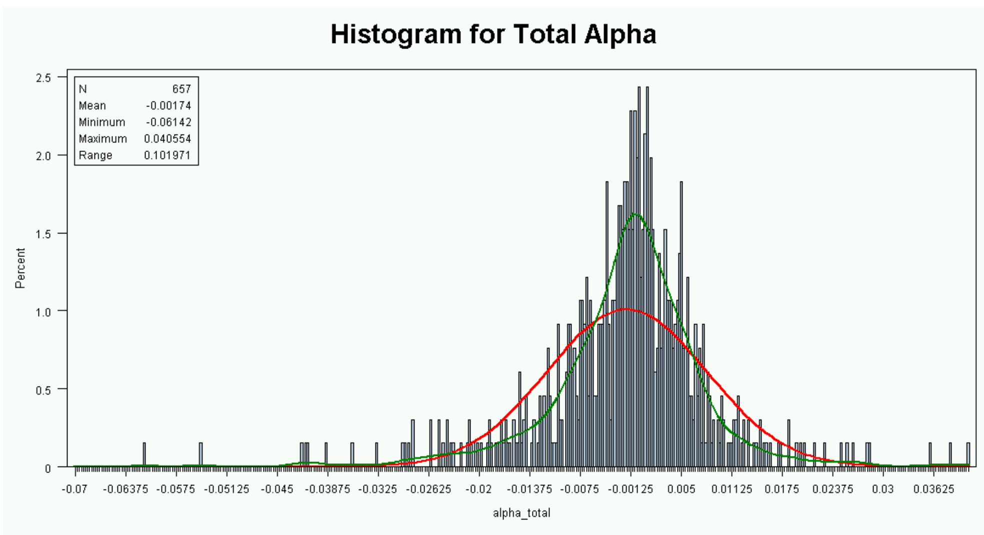


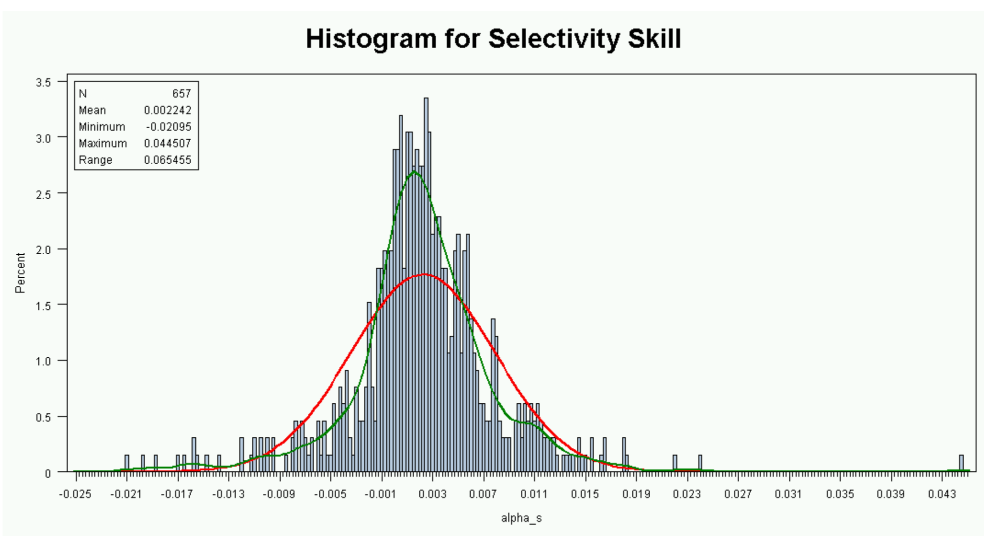
Reported are the monthly alpha estimates of yearly performance, the corresponding standard errors and t-statistics.

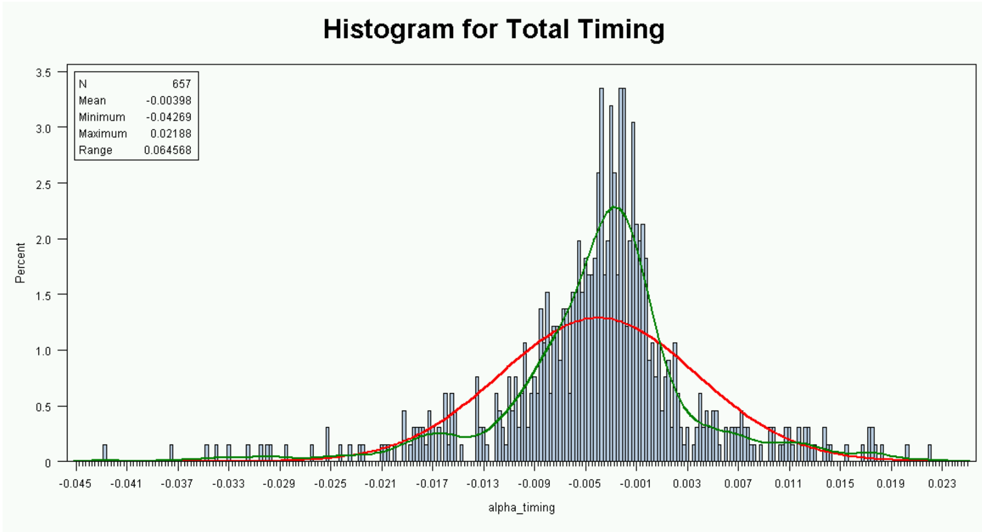
		1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Selectivity	Estimate	0.0022	-0.0008	-0.0012	0.0011	0.0001	-0.0029	0.0019	0.0012	0.0010	-0.0004	-0.0010	-0.0006	0.0014	-0.0002	0.0000	-0.0001
	StdErr	0.0020	0.0024	0.0011	0.0013	0.0009	0.0019	0.0024	0.0013	0.0012	0.0014	0.0008	0.0006	0.0008	0.0013	0.0014	0.0006
	t-value	1.06	-0.34	-1.14	0.86	0.14	-1.54	0.81	0.95	0.82	-0.27	-1.26	-1.03	1.77	-0.19	0.03	-0.09
Timing	Estimate	-0.0021	0.0006	0.0020	-0.0012	-0.0003	-0.0008	-0.0011	0.0013	-0.0028	-0.0016	-0.0002	-0.0001	-0.0001	0.0003	-0.0004	0.0001
	StdErr	0.0009	0.0014	0.0010	0.0017	0.0005	0.0027	0.0010	0.0008	0.0010	0.0013	0.0004	0.0002	0.0002	0.0002	0.0002	0.0004
	t-value	-2.28	0.45	1.98	-0.69	-0.63	-0.28	-1.02	1.70	-2.76	-1.30	-0.45	-0.47	-0.61	1.39	-2.23	0.32
Total	Estimate	0.0001	-0.0002	0.0008	-0.0001	-0.0002	-0.0036	0.0008	0.0025	-0.0018	-0.0020	-0.0012	-0.0007	0.0013	0.0001	-0.0004	0.0001
	StdErr	0.0022	0.0014	0.0008	0.0012	0.0008	0.0032	0.0022	0.0012	0.0013	0.0013	0.0009	0.0006	0.0009	0.0013	0.0013	0.0009
	t-value	0.05	-0.16	1.03	-0.08	-0.23	-1.11	0.38	2.01	-1.37	-1.58	-1.26	-1.13	1.53	0.04	-0.30	0.10
Liquidity	Estimate	-0.0003	0.0008	0.0008	-0.0005	0.0002	0.0007	-0.0014	0.0004	-0.0018	-0.0009	-0.0003	-0.0001	-0.0001	0.0003	-0.0004	-0.0003
	StdErr	0.0004	0.0014	0.0009	0.0006	0.0003	0.0023	0.0010	0.0007	0.0006	0.0005	0.0002	0.0002	0.0001	0.0001	0.0003	0.0002
	t-value	-0.79	0.52	0.98	-0.92	0.72	0.31	-1.41	0.52	-3.05	-2.08	-1.66	-0.61	-0.79	1.89	-1.13	-1.39
Market	Estimate	-0.0016	-0.0002	0.0015	-0.0003	-0.0005	-0.0006	0.0003	0.0009	-0.0011	-0.0005	0.0002	0.0001	0.0000	0.0000	-0.0001	0.0003
	StdErr	0.0008	0.0002	0.0009	0.0011	0.0003	0.0004	0.0004	0.0005	0.0008	0.0008	0.0004	0.0001	0.0000	0.0002	0.0004	0.0004
	t-value	-2.05	-0.71	1.70	-0.29	-1.75	-1.54	0.75	1.88	-1.38	-0.59	0.60	0.87	0.02	0.08	-0.13	0.74
Volatility	Estimate	-0.0002	0.0000	-0.0004	-0.0004	0.0000	-0.0009	0.0001	0.0000	0.0001	-0.0002	-0.0002	-0.0001	0.0000	0.0000	0.0000	0.0001
	StdErr	0.0001	0.0002	0.0002	0.0004	0.0001	0.0010	0.0001	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
	t-value	-1.23	0.05	-2.08	-1.00	-0.15	-0.87	0.47	-0.10	0.63	-3.44	-5.73	-1.83	1.21	-0.28	-0.43	1.12

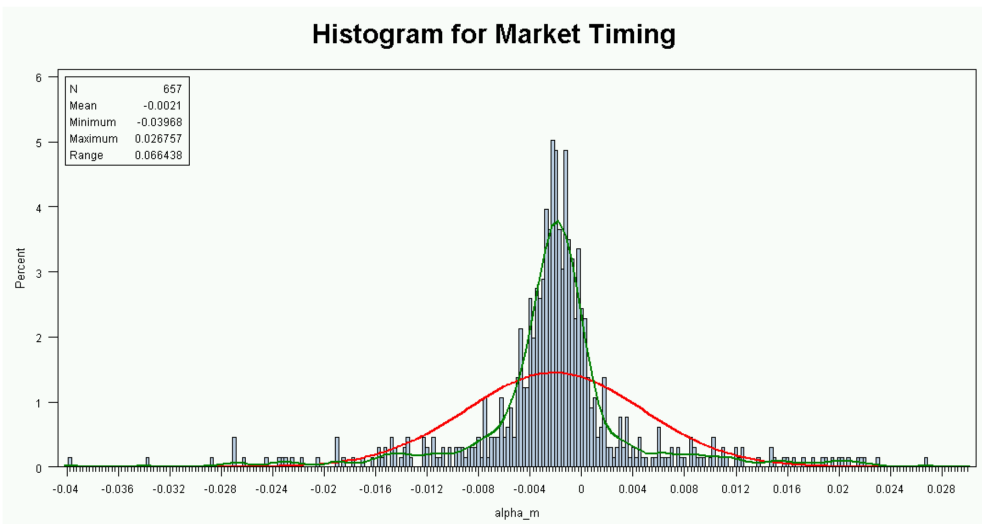
Figure 6. Distribution of individual fund alphas.

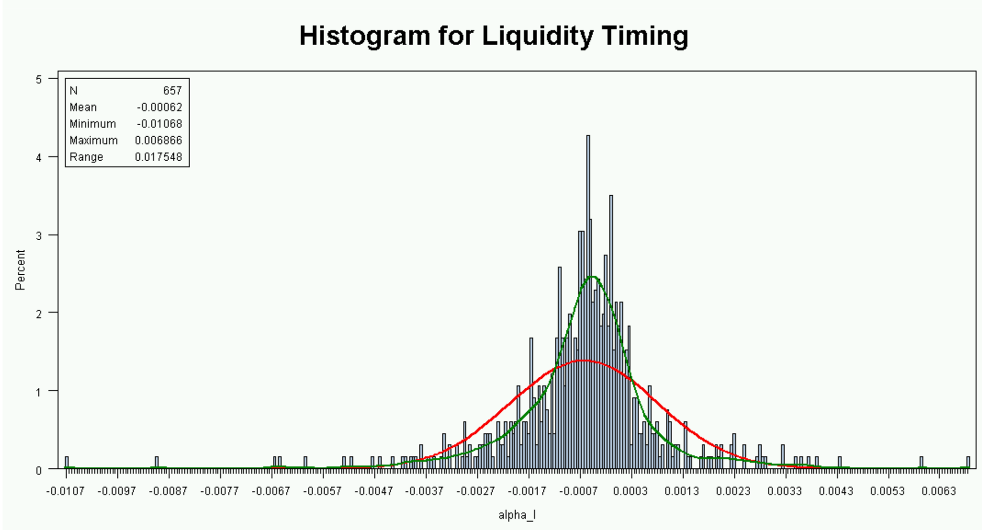
Histograms of monthly individual funds' alphas are depicted for each ability. Normal and kernel distributions are fitted. I estimate the individual funds' alphas by solving equations (6d) to (6f) subject to (6a) to (6c) and (6g) using the GMM method with a Newey-West lag of three. I apply prior quarter-end holdings information to the current quarter information. I require each fund to have at least 15 observations over the sample period January 1995 to December 2010.

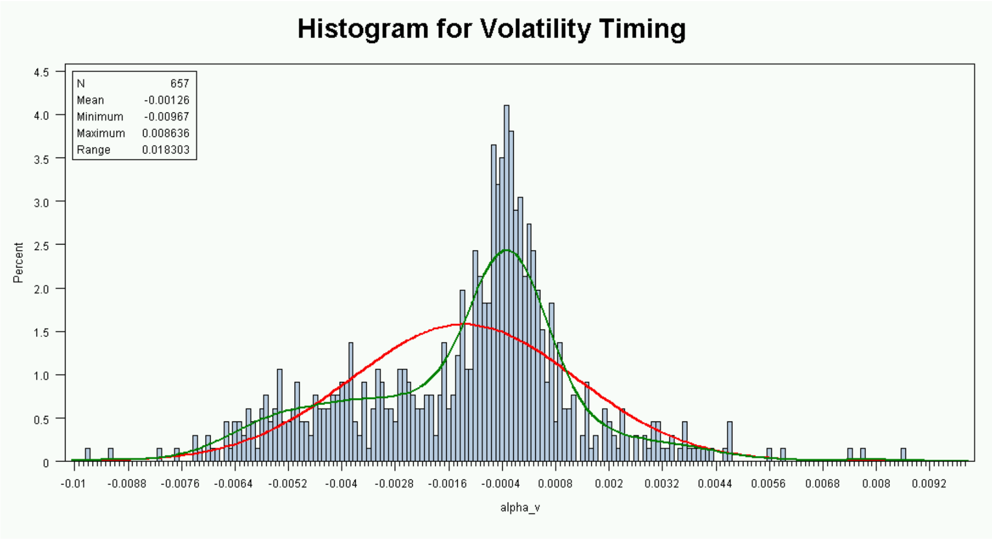





Histogram for Total Timing
N 657
Mean -0.00398
Minimum -0.04269
Maximum 0.02188
Range 0.064568
Percent
alpha_timing


Histogram for Market Timing
N 657
Mean -0.0021
Minimum -0.03968
Maximum 0.026757
Range 0.066438
Percent
alpha_m


Histogram for Liquidity Timing
N 657
Mean -0.00062
Minimum -0.01068
Maximum 0.006866
Range 0.017548
Percent
alpha_l



Histogram for Volatility Timing
N 657
Mean -0.00126
Minimum -0.00967
Maximum 0.008636
Range 0.018303
Percent
alpha_v

Table 8. Bootstrap Analysis.

I generate 1,000 hypothetical cross-sections of individual funds' alphas and the corresponding t-statistics under the assumption of no ability by randomly sampling with replacement monthly market returns, market liquidity risk, and stock idiosyncratic returns, with portfolio holdings, stocks' market-, and liquidity betas fixed. For each cross-section, I rank hypothetical alphas and the t-statistics, and then compare them to the corresponding actual ranked estimate and t-statistics. Reported are actual estimate, its t-statistic, and the empirical p-value for each ability and selected percentile. The empirical p-value for skill (luck) is computed by

$p_{value,\alpha} = \frac{\sum_i 1\{\alpha_{Hypothetical,\ i} > \alpha_{Actual}\}}{1,000}$, or $p_{value,t} = \frac{\sum_i 1\{t-stat_{Hypothetical,\ i} > t-stat_{Actual}\}}{1,000}$ (one less the empirical p-values for skill).

		Min	1st	5th	10th	25th	Med	75th	90th	95th	99th	Max
Selectivity	Actual Estimate	-0.021	-0.016	-0.007	-0.004	0.000	0.002	0.005	0.008	0.011	0.017	0.045
	p-value_skill	0.001	0.063	0.273	0.461	0.907	0.983	0.942	0.989	0.995	1.000	0.944
	p-value_luck	0.999	0.937	0.727	0.539	0.093	0.017	0.058	0.011	0.005	0.000	0.056
Timing	Actual Estimate	-0.043	-0.030	-0.018	-0.012	-0.007	-0.003	-0.001	0.004	0.009	0.017	0.022
	p-value_skill	0.192	0.444	0.606	0.600	0.703	0.829	0.929	0.570	0.481	0.685	0.928
	p-value_luck	0.808	0.556	0.394	0.400	0.297	0.171	0.071	0.430	0.519	0.315	0.072
Total	Actual Estimate	-0.061	-0.036	-0.018	-0.012	-0.006	-0.001	0.003	0.007	0.012	0.026	0.041
	p-value_skill	0.253	0.390	0.515	0.597	0.796	0.933	0.956	0.988	0.985	0.953	0.984
	p-value_luck	0.747	0.610	0.485	0.403	0.204	0.067	0.044	0.012	0.015	0.047	0.016
Liquidity	Actual Estimate	-0.011	-0.005	-0.003	-0.002	-0.001	-0.001	0.000	0.001	0.001	0.003	0.007
	p-value_skill	0.200	0.181	0.407	0.471	0.553	0.651	0.768	0.924	0.956	0.964	0.971
	p-value_luck	0.800	0.819	0.593	0.529	0.447	0.349	0.232	0.076	0.044	0.036	0.029
Market	Actual Estimate	-0.040	-0.026	-0.014	-0.008	-0.004	-0.002	0.000	0.004	0.010	0.020	0.027
	p-value_skill	0.264	0.434	0.566	0.501	0.541	0.713	0.875	0.618	0.457	0.573	0.754
	p-value_luck	0.736	0.566	0.434	0.499	0.459	0.287	0.125	0.382	0.543	0.427	0.246
Volatility	Actual Estimate	-0.010	-0.007	-0.006	-0.005	-0.003	-0.001	0.000	0.001	0.003	0.005	0.009
	p-value_skill	0.399	0.494	0.649	0.732	0.885	0.871	0.787	0.655	0.494	0.545	0.532
	p-value_luck	0.601	0.506	0.351	0.268	0.115	0.129	0.213	0.345	0.506	0.455	0.468

		Min	1st	5th	10th	25th	Med	75th	90th	95th	99th	Max
Selectivity	Actual t-statistic	-3.01	-2.20	-1.26	-0.81	-0.09	0.82	1.71	2.43	2.91	3.79	6.63
	p-value_skill	0.511	0.920	0.929	0.914	0.952	0.883	0.749	0.790	0.765	0.766	0.065
	p-value_luck	0.489	0.080	0.071	0.086	0.048	0.117	0.251	0.210	0.235	0.234	0.935
Timing	Actual t-statistic	-3.30	-2.14	-1.33	-1.03	-0.73	-0.48	-0.13	0.59	1.21	2.26	2.86
	p-value_skill	0.357	0.253	0.170	0.229	0.465	0.702	0.873	0.811	0.774	0.879	0.985
	p-value_luck	0.643	0.747	0.830	0.771	0.535	0.298	0.127	0.189	0.226	0.121	0.015
Total	Actual t-statistic	-4.81	-2.16	-1.32	-0.89	-0.54	-0.11	0.40	1.07	1.55	2.67	4.01
	p-value_skill	0.891	0.440	0.418	0.380	0.713	0.929	0.993	0.990	0.956	0.816	0.803
	p-value_luck	0.109	0.560	0.582	0.620	0.287	0.071	0.007	0.010	0.044	0.184	0.197
Liquidity	Actual t-statistic	-3.04	-2.66	-1.95	-1.66	-1.07	-0.60	-0.03	0.71	1.15	2.01	2.74
	p-value_skill	0.055	0.192	0.239	0.309	0.352	0.575	0.772	0.864	0.892	0.927	0.962
	p-value_luck	0.945	0.808	0.761	0.691	0.648	0.425	0.228	0.136	0.108	0.073	0.038
Market	Actual t-statistic	-2.94	-2.18	-1.38	-1.05	-0.61	-0.31	-0.05	0.53	1.21	1.98	2.97
	p-value_skill	0.173	0.210	0.190	0.274	0.467	0.615	0.837	0.833	0.684	0.871	0.921
	p-value_luck	0.827	0.790	0.810	0.726	0.533	0.385	0.163	0.167	0.316	0.129	0.079
Volatility	Actual t-statistic	-2.88	-2.70	-2.50	-2.29	-1.57	-0.55	0.09	0.91	3.18	13.79	26.66
	p-value_skill	0.091	0.364	0.711	0.874	0.970	0.887	0.854	0.958	0.465	0.096	0.069
	p-value_luck	0.909	0.636	0.289	0.126	0.030	0.113	0.146	0.042	0.535	0.904	0.931

Table 9. Performance Persistence.

For each year, individual funds are sorted into quintiles according to the prior year's performance or the entire performance history. Then the quintile portfolios, and the spread portfolio of going long for the top quintile portfolio and short for the bottom are formed using equal weight. I report the alphas for the portfolios rebalanced each year according to the prior performance and held for one year, and the corresponding t-statistic estimated using the GMM method with a Newey-West of lag three.

Panel A. Ranking of individual funds based on the prior year's performance requiring a full 12 months of observations for the prior year. To ensure that I have enough funds for ranking, I begin the evaluation period in 1997.

Ranked on prior year's total alpha												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0011	-0.32	-0.0014	-0.38	-0.0011	-0.32	-0.0013	-0.35	-0.0007	-0.16	-0.52%	-0.40
α_L	-0.0007	-0.65	-0.0005	-0.91	-0.0004	-1.08	-0.0007	-1.30	-0.0003	-0.55	-0.42%	-0.36
α_σ	0.0001	0.08	-0.0002	-0.18	-0.0004	-0.47	-0.0003	-0.43	-0.0005	-0.58	0.69%	1.15
α_S	0.0042	3.46	0.0028	3.00	0.0024	3.11	0.0011	1.23	0.0012	0.91	3.69%	2.20
alpha_timing	-0.0017	-0.38	-0.0020	-0.47	-0.0019	-0.47	-0.0023	-0.56	-0.0015	-0.32	-0.25%	-0.13
alpha_total	0.0025	0.53	0.0008	0.18	0.0005	0.13	-0.0011	-0.28	-0.0003	-0.07	3.44%	1.48

Ranked on prior year's selectivity alpha												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0012	-0.32	-0.0011	-0.31	-0.0012	-0.33	-0.0010	-0.27	-0.0012	-0.31	0.06%	0.08
α_L	-0.0008	-0.76	-0.0005	-0.98	-0.0007	-1.47	-0.0003	-0.78	-0.0003	-0.61	-0.57%	-0.55
α_σ	-0.0002	-0.24	-0.0003	-0.34	-0.0003	-0.33	-0.0004	-0.44	-0.0002	-0.18	-0.07%	-0.18
α_S	0.0043	3.26	0.0027	2.62	0.0016	2.07	0.0020	2.54	0.0011	0.86	3.92%	2.11
alpha_timing	-0.0022	-0.48	-0.0019	-0.45	-0.0021	-0.52	-0.0016	-0.39	-0.0017	-0.38	-0.58%	-0.42
alpha_total	0.0022	0.44	0.0008	0.18	-0.0004	-0.11	0.0004	0.09	-0.0006	-0.14	3.34%	1.43

Ranked on prior year's total timing alpha												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0017	-0.47	-0.0010	-0.28	-0.0011	-0.30	-0.0011	-0.29	-0.0009	-0.23	-0.95%	-0.60
α_L	-0.0007	-0.70	-0.0003	-0.50	-0.0005	-1.34	-0.0007	-1.11	-0.0005	-0.66	-0.18%	-0.15
α_σ	0.0006	0.56	-0.0002	-0.19	-0.0004	-0.44	-0.0006	-0.68	-0.0007	-0.92	1.55%	2.24
α_S	0.0031	2.54	0.0021	2.36	0.0027	3.18	0.0020	2.46	0.0020	1.49	1.42%	0.80
alpha_timing	-0.0018	-0.40	-0.0014	-0.34	-0.0020	-0.48	-0.0023	-0.53	-0.0021	-0.47	0.42%	0.18
alpha_total	0.0014	0.32	0.0006	0.15	0.0007	0.17	-0.0003	-0.07	-0.0001	-0.03	1.84%	0.83

Ranked on prior year's market timing alpha												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0006	-0.19	-0.0012	-0.33	-0.0012	-0.32	-0.0012	-0.32	-0.0014	-0.35	0.98%	0.47
α_L	-0.0006	-0.80	-0.0003	-0.64	-0.0007	-1.60	-0.0006	-1.13	-0.0005	-0.76	-0.18%	-0.42
α_σ	0.0003	0.36	-0.0002	-0.26	-0.0004	-0.49	-0.0004	-0.47	-0.0006	-0.65	1.06%	2.52
α_S	0.0032	2.70	0.0033	3.51	0.0013	1.85	0.0024	2.65	0.0015	1.15	2.04%	1.32
alpha_timing	-0.0009	-0.23	-0.0017	-0.41	-0.0023	-0.54	-0.0021	-0.50	-0.0025	-0.50	1.85%	0.80
alpha_total	0.0023	0.54	0.0016	0.39	-0.0010	-0.23	0.0003	0.07	-0.0010	-0.20	3.89%	1.81

Ranked on prior year's volatility alpha												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0022	-0.60	-0.0014	-0.38	-0.0015	-0.41	-0.0008	-0.21	0.0002	0.04	-2.79%	-1.50
α_L	-0.0005	-0.66	-0.0008	-1.49	-0.0005	-1.17	-0.0006	-1.02	-0.0002	-0.19	-0.43%	-0.31
α_σ	-0.0001	-0.05	-0.0002	-0.24	-0.0004	-0.42	-0.0004	-0.43	-0.0003	-0.37	0.33%	0.46
α_S	0.0020	1.76	0.0027	2.77	0.0023	2.80	0.0017	1.89	0.0031	2.20	-1.34%	-0.69
alpha_timing	-0.0028	-0.62	-0.0024	-0.57	-0.0023	-0.55	-0.0017	-0.39	-0.0003	-0.08	-2.90%	-1.15
alpha_total	-0.0007	-0.17	0.0003	0.07	0.0000	-0.01	0.0000	-0.01	0.0028	0.59	-4.24%	-1.47

Ranked on prior year's liquidity timing alpha												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0017	-0.46	-0.0012	-0.35	-0.0011	-0.31	-0.0008	-0.23	-0.0008	-0.20	-1.13%	-1.28
α_L	-0.0007	-0.69	-0.0005	-0.89	-0.0003	-0.65	-0.0004	-0.77	-0.0007	-0.74	0.05%	0.03
α_σ	0.0001	0.14	0.0000	-0.03	-0.0003	-0.40	-0.0005	-0.58	-0.0006	-0.68	0.88%	1.18
α_S	0.0015	1.23	0.0028	3.09	0.0031	3.45	0.0019	2.06	0.0025	1.88	-1.13%	-0.57
alpha_timing	-0.0023	-0.50	-0.0018	-0.43	-0.0017	-0.42	-0.0017	-0.41	-0.0021	-0.45	-0.20%	-0.09
alpha_total	-0.0007	-0.16	0.0010	0.25	0.0014	0.33	0.0003	0.06	0.0004	0.08	-1.34%	-0.55

Panel B. Ranking of individual funds based on the entire performance history, requiring at least 15 monthly observations during the history. To ensure that I have enough funds for ranking, I start the evaluation period in 1998.

Ranked on the total alpha from the entire history												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0020	-0.57	-0.0020	-0.54	-0.0021	-0.55	-0.0019	-0.49	-0.0022	-0.51	0.17%	0.17
α_L	-0.0004	-0.48	-0.0006	-1.15	-0.0004	-0.83	-0.0006	-1.02	-0.0004	-0.67	-0.06%	-0.07
α_σ	0.0000	-0.03	-0.0003	-0.29	-0.0003	-0.36	-0.0003	-0.37	-0.0002	-0.23	0.24%	0.63
α_S	0.0040	3.57	0.0030	3.47	0.0030	3.54	0.0026	2.19	0.0018	1.62	2.60%	1.72
alpha_timing	-0.0025	-0.56	-0.0029	-0.66	-0.0028	-0.63	-0.0028	-0.62	-0.0028	-0.56	0.35%	0.26
alpha_total	0.0015	0.31	0.0001	0.02	0.0002	0.05	-0.0002	-0.04	-0.0009	-0.19	2.95%	1.55

Ranked on the timing alpha from the entire history												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0026	-0.70	-0.0023	-0.60	-0.0015	-0.41	-0.0018	-0.47	-0.0021	-0.52	-0.04%	-0.45
α_L	-0.0006	-1.10	-0.0003	-0.69	-0.0006	-1.19	-0.0006	-0.77	-0.0003	-0.38	-0.03%	-0.60
α_σ	0.0000	-0.04	-0.0004	-0.41	-0.0003	-0.34	-0.0002	-0.23	-0.0003	-0.33	0.03%	1.22
α_S	0.0035	3.64	0.0024	2.65	0.0025	2.68	0.0037	3.11	0.0025	2.14	0.10%	0.87
alpha_timing	-0.0032	-0.72	-0.0029	-0.66	-0.0024	-0.56	-0.0026	-0.57	-0.0027	-0.57	-0.04%	-0.38
alpha_total	0.0003	0.06	-0.0006	-0.12	0.0001	0.02	0.0011	0.23	-0.0003	-0.05	0.05%	0.38

Ranked on the selectivity alpha from the entire history												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0017	-0.49	-0.0021	-0.55	-0.0019	-0.49	-0.0019	-0.47	-0.0025	-0.61	0.08%	1.00
α_L	-0.0006	-0.52	-0.0004	-0.73	-0.0006	-1.25	-0.0003	-0.71	-0.0007	-1.57	0.01%	0.16
α_σ	0.0000	-0.03	-0.0004	-0.50	-0.0003	-0.35	-0.0003	-0.34	-0.0001	-0.08	0.00%	0.11
α_S	0.0036	2.83	0.0029	3.46	0.0025	2.60	0.0025	2.88	0.0026	2.08	0.11%	0.84
alpha_timing	-0.0023	-0.52	-0.0029	-0.65	-0.0028	-0.63	-0.0025	-0.55	-0.0032	-0.68	0.09%	0.90
alpha_total	0.0013	0.27	-0.0001	-0.02	-0.0003	-0.06	0.0000	0.01	-0.0006	-0.13	0.20%	1.21

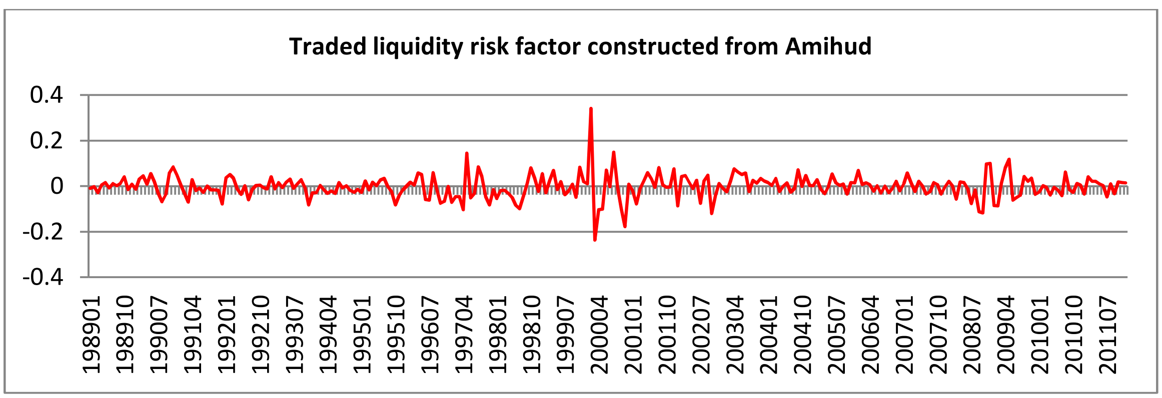
Ranked on the market timing alpha from the entire history												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0025	-0.66	-0.0020	-0.54	-0.0014	-0.38	-0.0021	-0.54	-0.0023	-0.56	-0.01%	-0.15
α_L	-0.0009	-1.10	-0.0004	-0.67	-0.0005	-1.03	-0.0005	-0.84	-0.0001	-0.28	-0.08%	-1.30
α_σ	-0.0002	-0.21	-0.0002	-0.23	-0.0004	-0.46	-0.0002	-0.17	-0.0003	-0.33	0.01%	0.54
α_S	0.0033	2.91	0.0030	2.83	0.0029	3.40	0.0029	2.87	0.0023	2.34	0.10%	1.14
alpha_timing	-0.0035	-0.77	-0.0027	-0.59	-0.0023	-0.53	-0.0028	-0.61	-0.0028	-0.58	-0.08%	-0.65
alpha_total	-0.0002	-0.05	0.0004	0.08	0.0006	0.14	0.0002	0.04	-0.0005	-0.10	0.03%	0.21

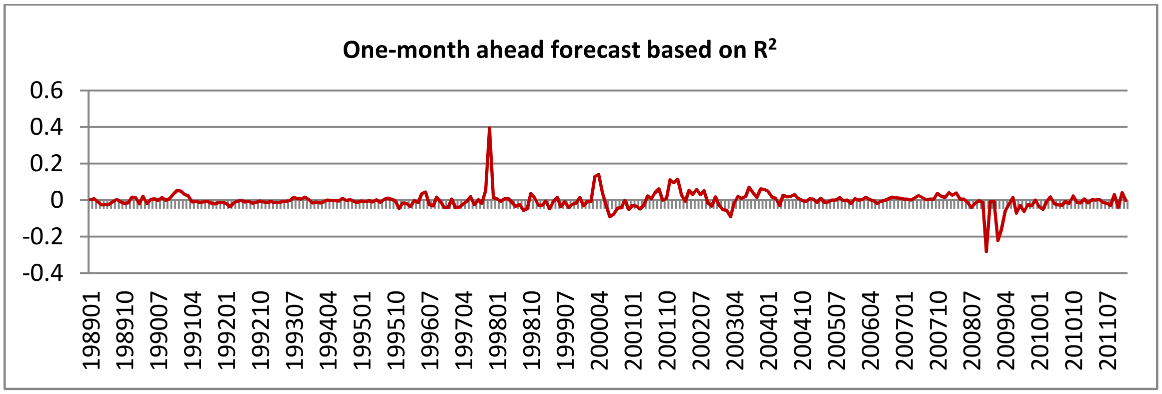
Ranked on the volatility timing alpha from the entire history												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0025	-0.62	-0.0020	-0.52	-0.0023	-0.61	-0.0019	-0.50	-0.0014	-0.36	-0.11%	-1.73
α_L	-0.0003	-0.32	-0.0005	-0.90	-0.0008	-1.37	-0.0001	-0.17	-0.0006	-0.88	0.03%	0.37
α_σ	-0.0002	-0.22	-0.0003	-0.38	-0.0002	-0.27	-0.0004	-0.46	-0.0001	-0.10	-0.01%	-0.62
α_S	0.0031	2.46	0.0027	2.92	0.0033	3.43	0.0030	2.95	0.0023	2.36	0.08%	0.73
alpha_timing	-0.0030	-0.61	-0.0028	-0.63	-0.0033	-0.75	-0.0023	-0.54	-0.0020	-0.46	-0.10%	-1.01
alpha_total	0.0001	0.03	-0.0001	-0.02	0.0000	0.00	0.0007	0.15	0.0003	0.07	-0.02%	-0.15

Ranked on the liquidity timing alpha from the entire history												
Parameter	1 (Best)		2		3		4		5 (Worst)		1-5	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	p.a.	t-value
α_M	-0.0021	-0.54	-0.0020	-0.53	-0.0020	-0.54	-0.0020	-0.54	-0.0020	-0.50	0.00%	-0.08
α_L	-0.0002	-0.28	-0.0004	-0.82	-0.0006	-1.36	-0.0005	-0.73	-0.0008	-0.64	0.06%	0.54
α_σ	-0.0001	-0.13	-0.0003	-0.38	-0.0003	-0.39	-0.0003	-0.29	-0.0002	-0.17	0.01%	0.18
α_S	0.0036	3.43	0.0022	2.46	0.0029	3.62	0.0024	2.74	0.0035	2.24	0.01%	0.10
alpha_timing	-0.0023	-0.51	-0.0027	-0.62	-0.0030	-0.68	-0.0028	-0.62	-0.0030	-0.59	0.06%	0.42
alpha_total	0.0013	0.27	-0.0005	-0.11	-0.0001	-0.02	-0.0004	-0.08	0.0005	0.10	0.08%	0.45

Figure 7. Predictability of liquidity

Panel A. Actual traded liquidity risk factor and one-month ahead forecast. For each month I run OLS regressions of traded liquidity risk factors on 2^9 (=512) possible combinations of the 9 publicly available information variables, using the prior 60 months of observations. My candidate variables include lagged traded liquidity risk factor, lagged book-to-market ratio (the ratio of book value to market value for the Dow Jones Industrial Average), lagged Treasury-bill rate (3-Month Treasury), lagged long-term yield (long-term government bond yield), lagged inflation rate (Consumer Price Index), lagged stock variance (sum of squared daily returns on the S&P 500), lagged CRSP spread value-weighted index, lagged dividend price ratio (the difference between the log of dividends and the log of prices), and lagged earnings price (the difference between the log of earnings and the log of prices). Among the 512 models, I choose the best regression model based on several model selection criteria such as AIC, BIC, and R^2. Then I make the one-month ahead forecast using current month's realized public information and the parameter estimates of the selected model.




One-month ahead forecast based on R²
0.6
0.4
0.2
0
-0.2
-0.4
198901
198910
199007
199104
199201
199210
199307
199404
199501
199510
199607
199704
199801
199810
199907
200004
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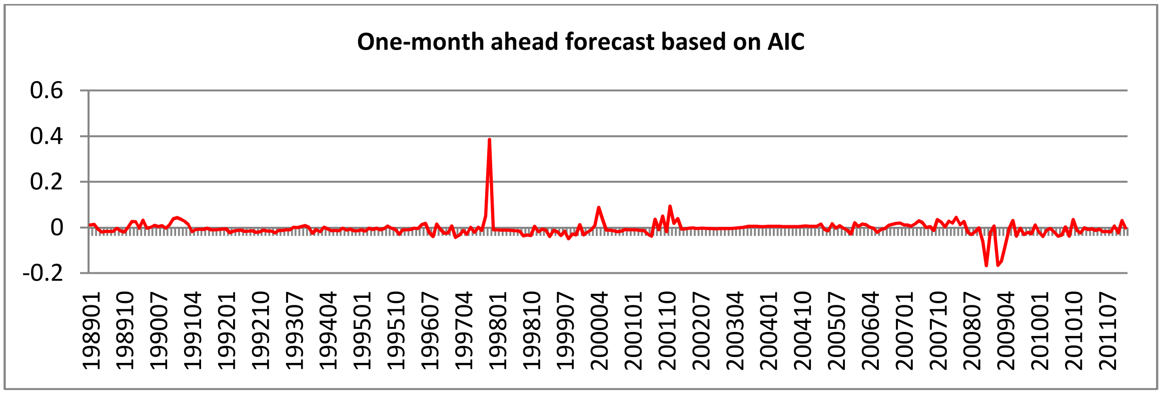
200904
201001
201010
201107


One-month ahead forecast based on AIC
0.6
0.4
0.2
0
-0.2
198901
198910
199007
199104
199201
199210
199307
199404
199501
199510
199607
199704
199801
199810
199907
200004
200101
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200207
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200401
200410
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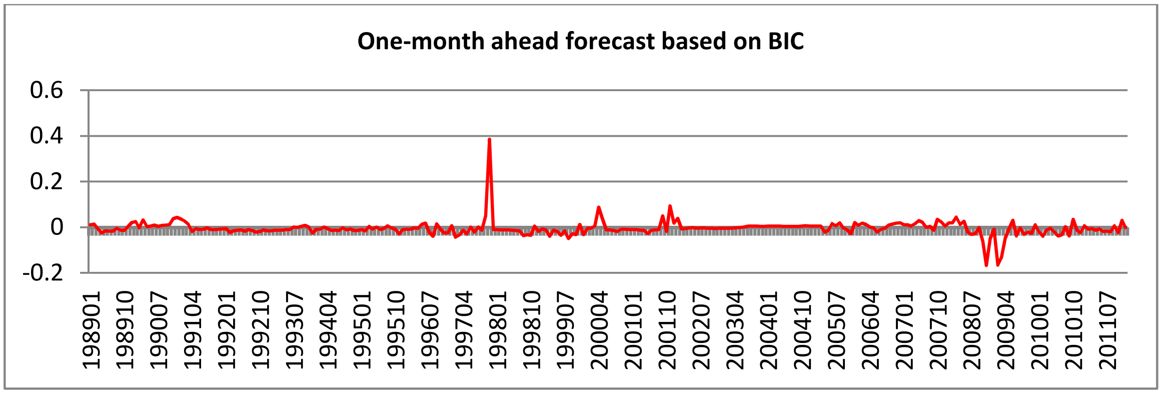
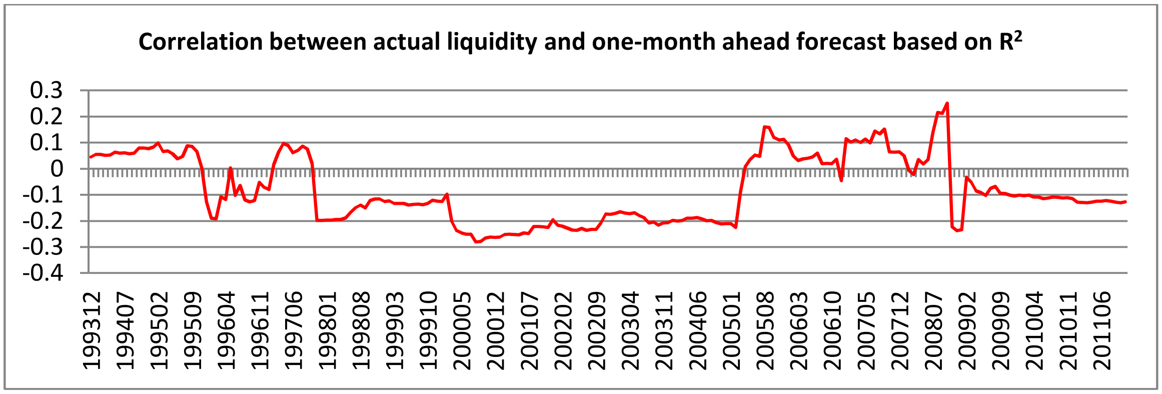
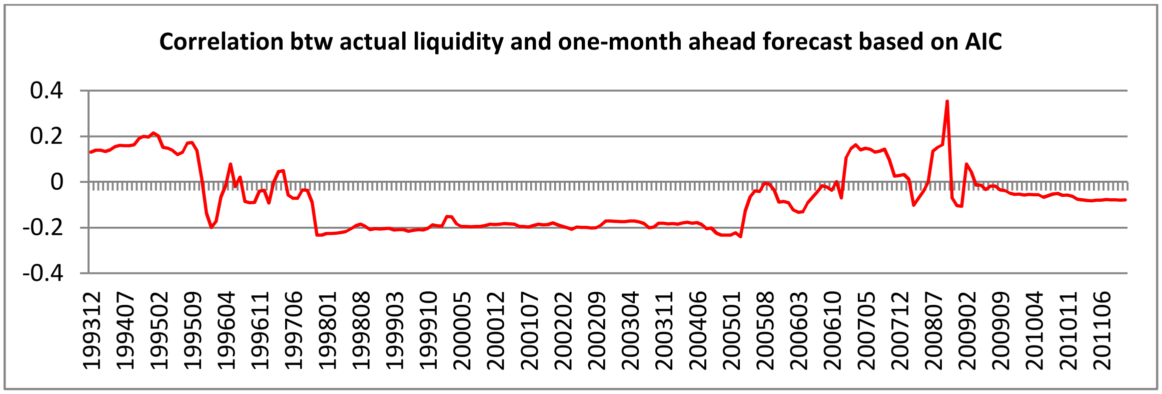
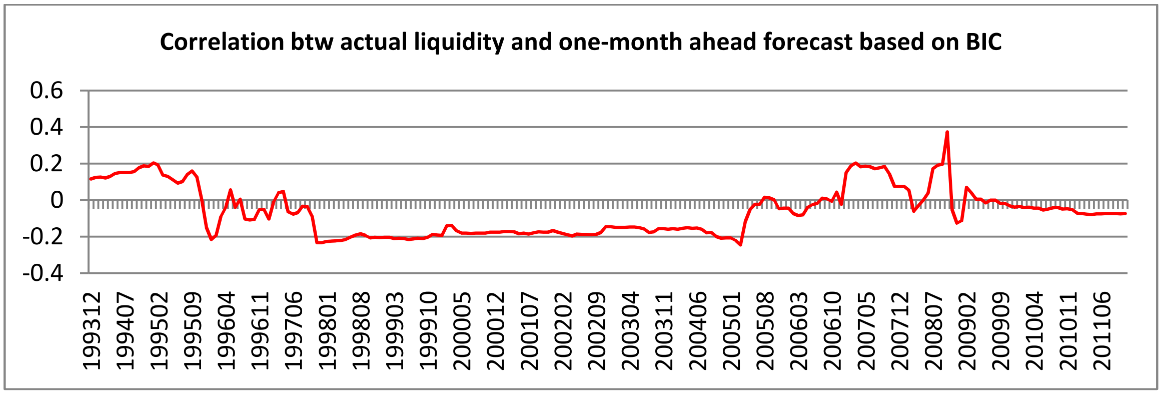
200604
200701
200710
200807
200904
201001
201010
201107


One-month ahead forecast based on BIC
0.6
0.4
0.2
0
-0.2
198901
198910
199007
199104
199201
199210
199307
199404
199501
199510
199607
199704
199801
199810
199907
200004
200101
200110
200207
200304
200401
200410
200507
200604
200701
200710
200807
200904
201001
201010
201107

Panel B. Pearson correlation coefficient of the actual traded liquidity risk factor and its one-month ahead forecast. For each month I use 60 monthly (current month and 59 prior months) observations to compute the recursive Pearson correlation coefficients between the actual traded liquidity risk factor and its one-month ahead forecast.

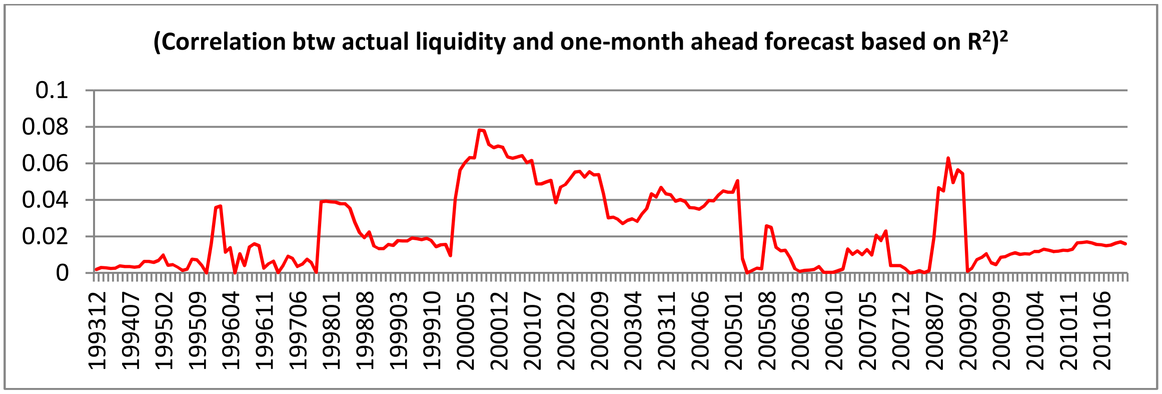


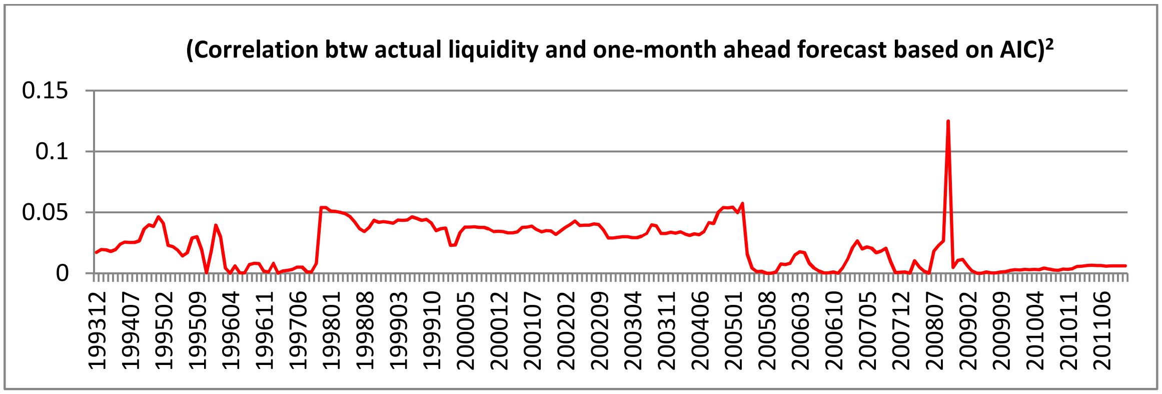


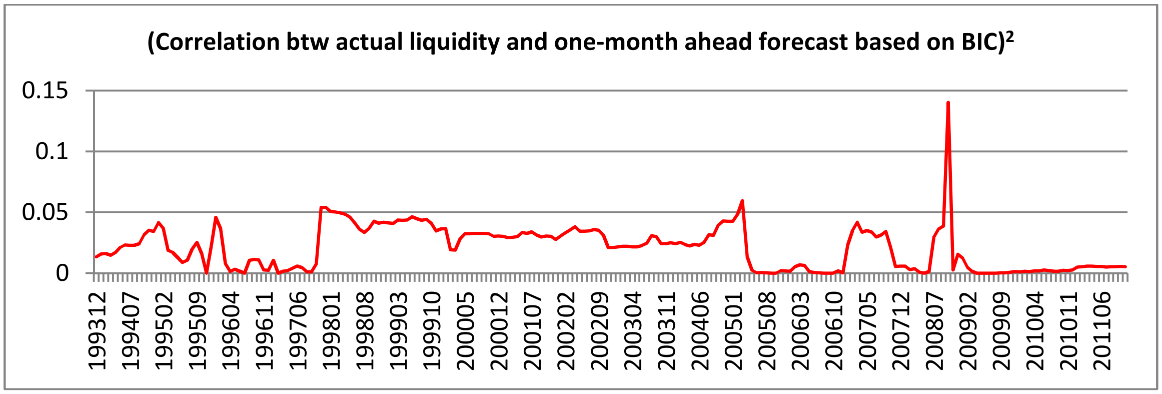


Panel C. Squared value of the correlation coefficient.

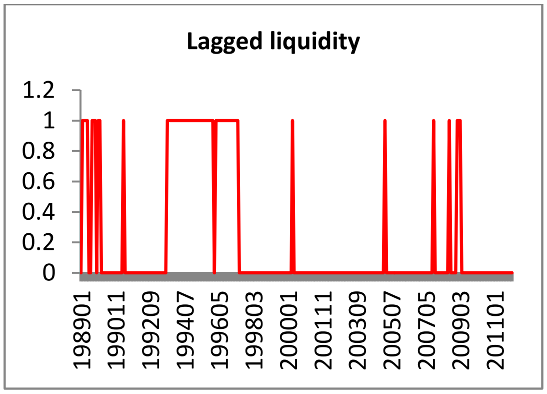
For each month I use 60 monthly (current month and 59 prior months) observations to compute the squared Pearson correlation coefficient between the actual traded liquidity risk portfolio return and its one-month ahead forecast.

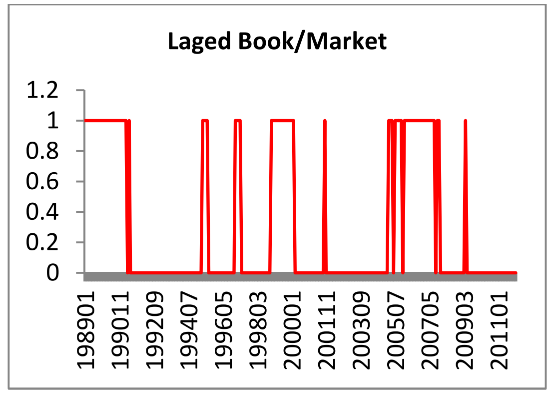


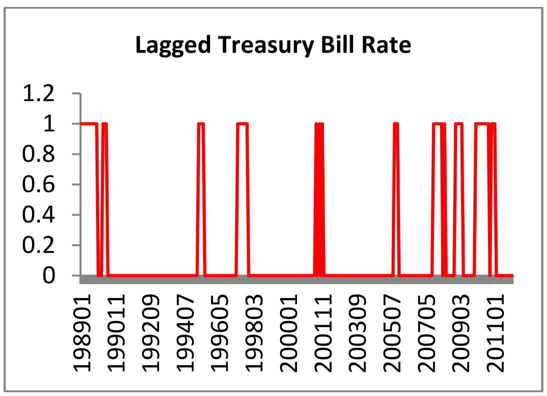


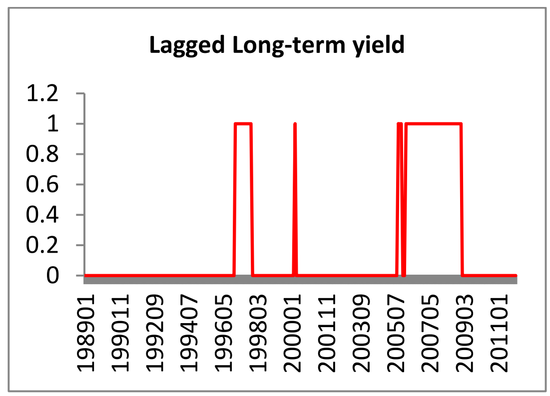


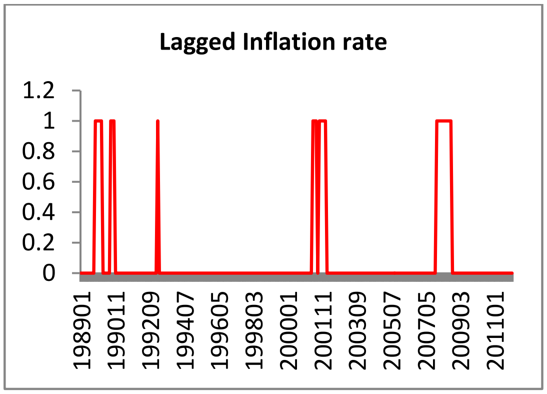
Panel D. Inclusion frequency of the variables in the best set under the AIC. For each variable, the table plots a dummy variable that equals one if the variable is included in the best model for the month, and zero otherwise. I report only the results based on AIC because the models chosen under the AIC and BIC give similar results, and the model selected under the adjusted R^2 almost always include all the 9 variables.







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0.8
0.6
0.4
0.2
0
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199209
199407
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200705
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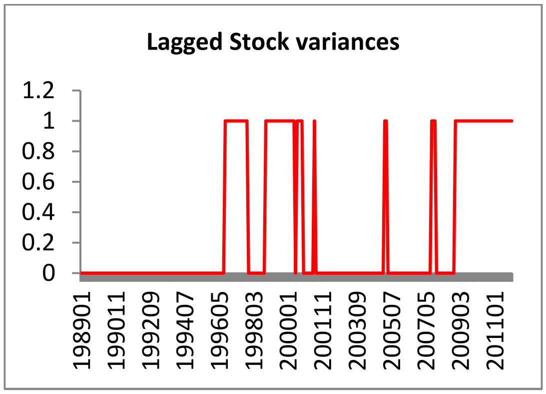
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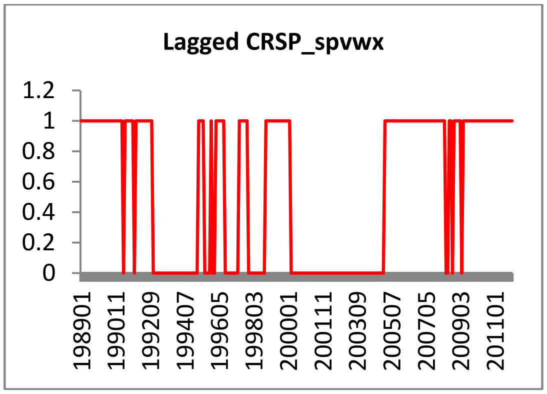
Lagged CRSP_spvwx
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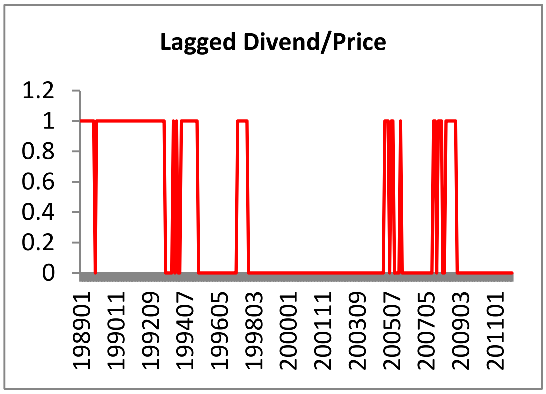
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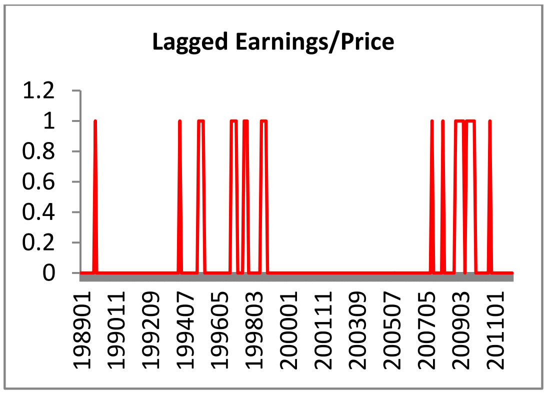
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