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Market Liquidity and Exposure of Hedge Funds

Abstract

We examine whether the drastic improvement in liquidity in the US stock market after 2003 has impacted the systematic exposures of hedge funds to the US-stock market. The relation between market exposure and Amihud's illiquidity measure reverses significantly around a breakpoint situated somewhere around 2003. The results are robust to different fund selection criteria, volatility timing, the presence of illiquid holdings and the exact position of the break point. Using the returns to a pairs trading strategy as a sorting criterion for creating portfolios, we find that the effect is strongest for funds that have a significantly positive loading on the pairs trading return. The results suggest that before 2003, time-varying illiquidity led to a time-varying long bias in US-stock market exposure. The reversal of the relationship points towards liquidity timing by hedge funds in the most recent period, after the introduction of automated trading on the New York stock exchange in March 2003.

Keywords: hedge funds, market liquidity, limits to arbitrage, liquidity timing, pairs trading

JEL-Classification: G12, G23.

1 Introduction

In 2003, the New York Stock Exchange (NYSE) finalized a change in market structure with the introduction of Autoquote, an automated trading system. The findings of Hendershott et al. (2011) show that this change had a large impact on the cost of trading. Not only did the transition to Autoquote lower spreads, but it also facilitated algorithmic trading in a major way. The bid-ask spreads and other measures of the market impact of trading decreased markedly in 2003. The finding of Hendershott et al. is illustrated in Figure 1, where we show the evolution over time of Amihud's (2002) illiquidity measure, a proxy for the price impact of trading and used throughout this paper. We can clearly see that the costs of trading and associated liquidity of the stock market improved drastically after 2003. One likely group of market participants that is expected to be influenced by this general and widespread improvement in stock trading, are hedge funds. Equity-oriented hedge funds are known for their dynamic trading strategies and the advent of electronic trading has seen a surge of interest in algorithmic trading, much of which is performed by hedge funds. In this paper we study the relationship between the stock market exposure of hedge funds and market liquidity and test whether it changed over time, specifically before and after 2003.

Hedge funds assets have grown tremendously the last decade, but their short average lifespan and lavish compensation of managers begs the question of the real benefits to the financial system. The disappointing performance over the credit crisis, their role in bidding up CDO prices, as well as the alleged short selling of bank's shares during the crisis, makes the question of the sources of performance and systematic risk all the more relevant.

The systematic risk of hedge funds is not straightforward to measure. Hedge funds can change exposures quickly or use derivatives so that the relationships with traditional asset classes is highly nonlinear, see example Fung and Hsieh (1997), Agarwal and Naik (2004), Mitchell and Pulvino (2001), Fung and Hsieh (2001), Bollen and Whaley (2009). Also, there are issues in reported returns, such as survivor and backfill-bias

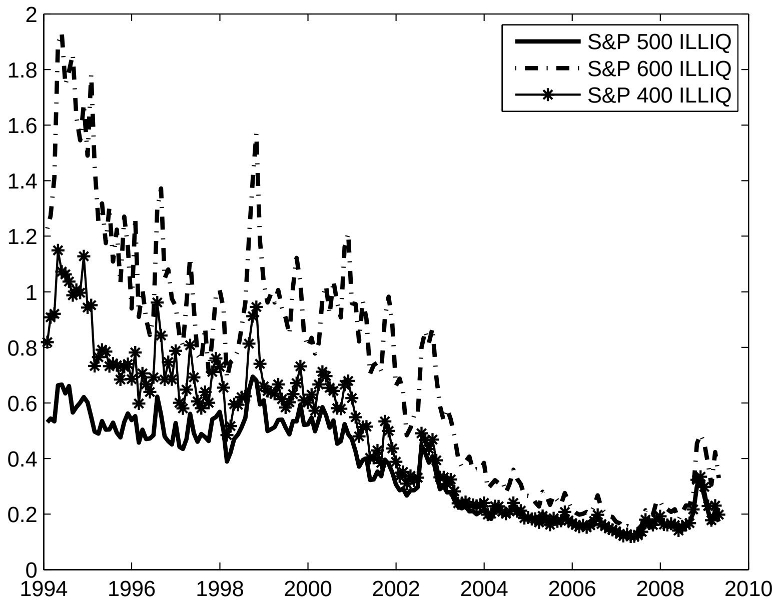


Figure 1: Market liquidity

The graph shows the monthly median of Amihud's ILLIQ measure for all the stocks in the S&P 500, S&P 400 (Midcap) and S&P 600 (Smallcap), respectively.

(Posthuma and Sluis (2003),Liang (2000)), serial correlation due to valuation models for illiquid assets, return smoothing or outright misreporting (Getmansky et al. (2004), Asness et al. (2001), Bollen and Pool (2009)). In addition, the relatively short lifespan of hedge funds prohibits modeling the time-variation in exposure to many risk factors. Thus, like in Patton (2009) we restrict our study of changing market exposure to the US stock market as a risk factor for hedge funds.

Patton (2009) finds some evidence that market neutrality is time-varying. Also, Sadka (2009) suggests that the outperformance of hedge funds can be partly explained by their high exposure to innovations in market liquidity. Thus, while hedge fund trading strategies generally lead to a low systematic risk relative to a broad US stock index, a time-varying component might remain, possibly caused by the impact of market illiquidity on profit opportunities and feasibility of trade strategies. In times of liquidity crises, hedge funds are particularly hurt by the low liquidity, be it driven by limits to arbitrage or the drying-up of funding, see Ben-David et al. (2010) and Aragon and

Strahan (2010).

The interaction between market liquidity and systematic risk is related to the issue of *systemic* risk. On the one hand, there is a clear positive role for hedge funds as providers of liquidity, or even 'lenders of last resort' (Brophy et al. (2009)). On the other hand, hedge funds receive some blame for financial turmoil like the Asian crisis of 1997 or the dot-com bubble of 2000. Although in both cases no dominant role for hedge funds can be proven, see Brown et al. (2000) and Brunnermeier and Nagel (2004), they have played a prominent role in the run-up to the credit crisis. Khandani and Lo (2007) explain the August 2007 market turmoil as the result of widely used quant strategies by hedge funds, with a sudden exogenous shock leading to a margin spiral such as described by Brunnermeier and Pedersen (2009).

As Patton (2009) suggests, we have only few choices in choosing a 'market' variable for market exposure. The median lifespan of a hedge fund is quite short so our market model needs to be parsimonious. We follow Patton in taking the return on the S&P 500 as the market return. We test the sensitivity of our results with the S&P 400 (MidCap) and S&P 600 (SmallCap).

Our paper is related to the work of Patton (2009), who operationalizes several neutrality measures for hedge funds, relative to the S&P 500. We complement this line of research by examining the impact of market liquidity on the ability of hedge funds to maintain a market neutral profile. Further, there has been a lot of interest in recent literature on modeling time variations in hedge fund risk exposures. Bollen and Whaley (2009) apply an optimal change-point regression that allows for discrete shifts in parameter values. They find that this parsimonious specification outperforms a stochastic beta model that is in general unable to capture discrete shifts in factor loadings. Patton and Ramadorai (2010) employ a similar methodology, enhanced by introducing high frequency variations in the conditioning variables. Both studies concentrate on explaining the dynamics of optimal exposures over a vast array of candidate factors. In this paper we focus exclusively on hedge fund market exposure and its interactions with market-wide liquidity. Cao et al. (2009) provide evidence of the liquidity timing ability of hedge fund managers who change their market exposure in line with market liquidity conditions, reducing it during periods of liquidity dry-ups. Ben-David et al. (2010) provide evidence of the latter fact, pointing towards a reduction in equity holdings of hedge funds during liquidity crises. In addition to the market timing hypothesis, however, we supply some evidence on the ability of hedge funds as arbitrageurs to provide liquidity during times of low market liquidity by expanding their market exposure or to absorb liquidity by unwinding their positions, in line with the limits to arbitrage hypothesis.

The main findings of our empirical investigation are as follows. We find a positive relationship between market illiquidity and the market exposure of hedge funds prior to 2003. For the period 2003 - 2009 we find the opposite pattern. This result is robust to volatility timing and the possibility of illiquid holdings. Furthermore, a changepoint regression points to the period 2000 - 2003 as where the most funds have a significant shift in exposure. These findings are in correspondence with Jylha et al. (2010), who find a distinct difference in the loading on the return to a liquidity timing strategy, before and after 2003. We conjecture that the source of hedge fund returns, and their impact on market liquidity, has undergone a structural change in the beginning of the 21st century. Implementing a pairs trading strategy like that of Gatev et al. (2006) shows that funds that load significantly on the pairs trading strategy show the effect all the stronger, while the effect partly disappears for funds that do not load on pairs trading.

The paper proceeds as follows. Section 2 describes the data. Section 3 performs time-series regressions of market exposure and liquidity. Section 4 explores the results when we select funds based on their exposure to a dynamic trading stratey. Section 5 checks the robustness for 2003 as a break point in hedge fund systematic market exposures. Section 6 concludes.

2 Data

For the hedge fund returns we use monthly returns and asset values of individual hedge funds from the Lipper TASS database as provided by Thomson Reuters. We use both live and graveyard funds. We follow the convention of starting in the year 1994, to avoid the most serious measurement biases, see Fung and Hsieh (2002). Our sample period is January 1994 until April 2009.

We apply the following filter to the individual funds. We discard funds that do not report in US-dollars, have assets below $10 million or have less than 24 consecutive months of data. We discard the first 12 months to account for backfill-bias. Unless stated otherwise, we select hedge funds from the style classifications 'Equity Market Neutral' and 'Long/Short Equity Hedge', so that our selection includes the US-equity market as primary focus.

For stock market index-returns we use the monthly total return on the S&P 500, S&P 400, and S&P 600, as provided by Datastream. For the construction of ILLIQ we use individual stock returns from the Center for Research in Security Prices (CRSP). To construct the monthly ILLIQ measure for each stock, we use daily data (returns, volume and market capitalization) for the constituents of each of the S&P indices (small cap S&P 600, mid cap S&P 400 and large cap S&P 500) for the 1994 - 2009 period. To obtain a market-wide illiquidity measure, we take the median of the individual ILLIQ measures across all stocks for each month.

The risk factors used in the change-point regressions are the seven factors from Fung and Hsieh (2004), as provided on the website of David Hsieh.

A summary of the data is in Table 1. The aggregate ILLIQ measure is in Figure 1.

[INSERT TABLE 1 HERE]

[INSERT FIGURE 1 HERE]

Looking at Figure 1 we can observe a change in the pattern of ILLIQ, which conforms with the idea of mid-2003 being a watershed for market participants that are sensitive to the market-impact of their trades, such as hedge funds. We hypothesize that the transition of NYSE is an important driver of this observation, see Hendershott et al. (2011).

3 Time-series regressions of market exposure and liquidity

We start with the most straightforward test of market exposure by estimating a time-series model for a hedge fund portfolio return with time-varying exposure, as in

$$R_t = \alpha_i + \beta_t r_{m,t} + \sum_k \gamma_k F_{t,k} + \varepsilon_t, \tag{1}$$

where R_t is the hedge fund portfolio return in month t, $r_{m,t}$ the return on the market and $F_{t,k}$ are the returns on the 7-factor model of Fung and Hsieh (2004) augmented by innovations in illiquidity to account for priced liquidity risk. The time-variation in β_t is captured by

$$\beta_t = \beta_0 + \beta_1 \cdot ILLIQ_t + \beta_2 \cdot VIX_t, \tag{2}$$

where $ILLIQ_t$ is Amihud's (2002) illiquidity measure and VIX_t the CBOE VIX index. Including the latter makes sense when we want to account for the fact that market exposure might be related to investor risk aversion, which is captured by the VIX.

We use the Amihud (2002) ILLIQ to measure stock market *illiquidity.* ILLIQ measures the average daily ratio of absolute stock return to dollar volume, representing the average price impact of a given dollar volume of a transaction. Among daily proxies, the Amihud liquidity measure is the most strongly correlated measure with intra-day measures of the price impact of trading, see Goyenko et al. (2009), De Jong and Driessen (2006), Hasbrouck (2009) and Korajczyk and Sadka (2008).

We measure overall stock market illiquidity as the per-stock ILLIQ-measure, weighted by market capitalization, as in

$$ILLIQ_t = \frac{1}{N_t} \sum_{i=1}^{N_t} ILLIQ_{i,t} \cdot M_{t-1}/M_0, \tag{3}$$

where N is the number of stocks in month t, M_t is the market capitalization at the end of month t and M_0 is the market cap at the beginning of the sample period. $ILLIQ_{i,t}$ is the ILLIQ measure for stock i in month t and is estimated as

$$ILLIQ_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|r_{i,t}^d|}{V_{i,t}^d}, \tag{4}$$

where D_t denotes the number of trading days in month t, $r_{i,t}^d$ denotes the return on stock i in the d^{th} day of month t, and $V_{i,t}^d$ denotes the dollar trading volume for stock i in the d^{th} day of month t. ILLIQ can be interpreted as the daily price response associated with one dollar of trading volume, and serves as a rough measure of price impact, see Amihud (2002).[1]

For comparison, we also consider the liquidity measure of Pastor and Stambaugh (2003), which is popular in the asset pricing literature. This measure, which we abbreviate as PS, measures the impact of today's signed volume on tomorrow's excess return. It is defined as the OLS-estimate of $\gamma_{i,t}$ in

$$r_{i,d+1,t}^e = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} \text{sign}(r_{i,d,t}^e) \cdot v_{i,d,t} + \varepsilon_{i,d+1,t}, \tag{6}$$

where for stock i on day d in month t, $r_{i,d,t}$ is the stock return, $r_{i,d,t}^e$ the excess return and $v_{i,d,t}$ the dollar volume. The estimated $\hat{\gamma}_{i,t}$ measures the short-term (one-day) reversal as a fraction of signed volume, and is negative, see Pastor and Stambaugh (2003). The higher (less negative) γ is, the more liquid a stock is. We use the PS measure as provided by CRSP.

[1]The above defined measure of market liquidity might suffer from outliers: small stocks that have extremely low volumes in one or more days. Acharya and Pedersen (2005) propose the normalized version of ILLIQ:

$$ILLIQ_{i,t}^{AP} = \min(0.25 + 0.30 \cdot ILLIQ_{i,t}, 30.00), \tag{5}$$

i.e., a scaled version of ILLIQ with a maximum of 30. The results remain qualitatively unchanged and are not reported in the current version in the paper for brevity.

Table 2 gives the estimation results for a time-series regression with a market return and an interaction term of the market with illiquidity, and the 7-factor returns of Fung and Hsieh (2004). The table runs until December 2008, which is the latest month for which CRSP has the Pastor-Stambaugh liquidity measure, which we want to include for comparison.

[INSERT Table 2 HERE]

Panel A of Table 2 shows that for the whole sample period, the interaction term of market times illiquidity is positive and significant. Thus a positive shock in aggregate market illiquidity leads to an increase in the market exposure of hedge fund portfolios. This finding is robust to adding the VIX index as a factor driving the time variations of market betas, as well as to the inclusion of innovations in liquidity, which are known to be priced in the cross-section of hedge fund returns. Further, the presence of illiquid holdings in hedge fund portfolios could potentially bias the market beta estimates, thus we also correct for this by including two lags of the market return in the regression, following Cao et al. (2009). Our findings remain robust to that correction as well. Interestingly, when using the Pastor-Stambaugh measure of liquidity we find no significant results for the interaction term.

Panel B shows the results for the first subperiod, split at June 2003, i.e., right after the introduction of Autoquote at the New York Stock Exchange. With respect to ILLIQ as market illiquidity measure, a significant switch in the relationship between market exposure and market-wide illiquidity is visible. Before 2003, hedge fund market exposure is positively related to illiquidity, suggesting that hedge funds are net suppliers of liquidity. In times with high illiquidity the market exposure is higher, and vice versa. Thus, hedge funds are in the market when liquidity is low. This suggests a positive role for hedge funds in the period before 2003, in accordance with the role of hedge funds in the Asian currency crisis of 1997, see Brown et al. (1998). Brown et al. remark on the role of hedge funds that "If anything, it appears that the top ten hedge funds were buying into the Ringgit as it fell in the late summer and early fall of 1997".

Panel C of Table 2 shows that, after 2003, the relationship between market betas and illiquidity is significantly negative. This is evidence of a liquidity timing interpretation of hedge funds' behavior, as in Cao et al. (2009) and Ben-David et al. (2010). An equivalent typology is that of demanding liquidity: hedge funds are more active in the market in times of high liquidity.

Hedge fund returns are known to exhibit significant serial correlation due to illiquid holdings in hedge fund strategies or smoothing of reported returns on the part of hedge fund managers (e.g. Getmansky et al. (2004)). We partially correct for the market beta bias induced by return smoothing by including lagged market returns in the regression model. Further, we also proceed by unsmoothing hedge fund returns following the methodology introduced in Amvella et al. (2010). It has the advantage of not imposing the same order of serial correlation for all return series, as it applies the appropriate unsmoothing profile for each fund. As well, it relies on a method of moments approach and thus does not impose assumptions on the distribution of hedge fund returns. Results for unsmoothed returns are reported in Table 3. Our previous finding still holds: hedge fund managers display a significant liquidity timing ability in the most recent period after 2003, while their market exposure remains significantly positively related to illiquidity prior to that.

[INSERT Table 3 HERE]

An additional test is provided by performing individual fund regressions. We first split all hedge funds in our sample in three subsamples, based on their exposure to a large-, small- and mid-cap market index, as proxied by S&P 500, S&P 600 and S&P 400. Selection of the index associated with each fund is based on Akaike's Information Criterion (AIC). We impose the additional requirement that each fund has at least 24 consecutive observations of return history, after eliminating the first 12 observations to mitigate backfilling bias. We then estimate our time-series model for each fund in the sample, using the corresponding market factor for each fund. The ILLIQ factor is also computed using the constituents of either S&P 500, S&P 600 or S&P 400. Results are presented in Table 4 where we show the average coefficient and t-statistic for the interaction term of market times ILLIQ for the individual fund regressions on the risk factors. We also report the cross-sectional t-statistic to measure whether the average loading over the funds in the sample is significantly different from zero, as in Chordia et al. (2000), Sadka (2009).

[INSERT Table 4 HERE]

Panel A of Table 4 shows a negative coefficient on the interaction for the full sample period. Also, the cross-sectional t-statistic has a large negative value, suggesting that the average coefficient is negative. However, there is a large heterogeneity between funds: depending on the selection of funds, between 7 and 11% of funds have a significant positive coefficient on the interaction term and between 15 and 25% have a negative loading. Moreover, panel B and C of Table 4 show that the balance of the fraction of funds loading positive and negative flips over the two subperiods. Panel B shows that the mean coefficient is on average positive for the period 1996-2003, while the fraction of funds with a significant positive coefficient on the interaction term is larger than for those with a negative coefficient. The opposite holds for panel C, where the sample shows more negative than positive coefficients. Thus, the individual fund regressions confirm the time-series regressions for the portfolios, and suggest a significant switch in exposure on the interaction term around the year 2003.

4 Time-varying market exposures through dynamic trading strategies

The reversal found in the systematic exposure to the stock market around 2003 could be caused by a number of factors. But foremost, it is a feature of the returns data of hedge funds. Since we know that hedge funds employ dynamic strategies, we test whether hedge funds that load significantly on returns to dynamic strategies are also more likely to show the reversal in market exposure.

Specifically, we are constructing the returns to a momentum strategy and a pairs trading strategy. We know that timing strategies that exploit momentum and reversal effects generate time-varying exposures to risk factors, see Blitz et al. (2011), so the use of these strategies by hedge funds might indicate which funds have a time-varying market exposure that is related to market liquidity.

The momentum strategy exploits the momentum in stock returns, i.e., the persistence in performance of past winners and losing stocks, see Jegadeesh and Titman (1993), Korajczyk and Sadka (2004). Returns to strategies that exploit momentum seem to deliver an excess return when correcting for systematic risk, found for several other stock markets and are present for most time periods. Here, we take the Fama-French momentum factor as provided by Kenneth French on his website.

The other strategy we consider, pairs trading, is a Wall Street quantitative investment strategy to perform statistical arbitrage between stocks with similar price histories. The strategy is shown to deliver persistent outperformance, correcting for the standard risk factors, see Gatev et al. (2006) and Engelberg et al. (2009). Pairs trading is also a speculative strategy in the sense that it relies on the implied convergence between prices that share statistical properties, with no particular fundamental reason why they should converge. Hence it is just one of many arbitrage strategies that can be employed by hedge funds. However, since it is well-known and straightforward to implement, we take the setup of Gatev et al. to mimic the typical return on a hedge fund trading strategy. We then form portfolios of hedge funds based on their exposure to the pairs trading return and estimate their conditional market exposure.

We generate pairs trading-returns along the line of Gatev et al. (2006) and give a short summary here. The full description is in the appendix. At the beginning of each month, we rank pairs of stocks from the NYSE-Amex-NASDAQ universe based on the sum of squared deviations of the normalized price indices over the past 12 months (the formation period). Only stocks with a full price history over the formation period are considered. This list of pairs is monitored during a period of six months (trading period) to detect a widening between prices of more than two standard deviations. The day after such an event, the pair is 'opened' by going one dollar short in the higher-priced stock and one dollar long in the lower-priced stock. A pair is closed once the prices cross or at the end of a 6-month trading period. The return on a pair is computed as the reinvested payoffs during the trading interval. A pair can open and close several times during the trading period. Given that we take a six month trading period, it is assumed that six strategies (managers) are operating simultaneously, in overlapping (six month) periods. We follow Engelberg et al. (2009) in that we also consider a strategy that closes out pairs that do not converge after 10 days[2].

We deviate from Gatev et al. (2006) in a number of ways. First, instead of computing portfolio returns over actual capital employed, we assume that each manager has a given amount of capital that he can use. Any capital not used (because too few pairs are open) is invested in S&P index futures. This is in accordance with empirical observations that hedge funds have a net long bias in the stock market. For example, Brunnermeier and Nagel (2004) show that hedge funds were invested in technology stocks in the same proportion as the market portfolio. Second, we put in two modeling assumptions on the extent to which pairs trading is employed by the hedge fund sector: at the beginning of a six-month trading period, the manager can employ capital equal to five percent of total market volume. On top of that, he can only invest a maximum of 40% of a pair's total dollar volume in a pair. These assumptions reflect the fact that (i) capital involved in pairs trading depends on total market volume, and (ii) the number of pairs that can be traded depends on the trading volume of the individual stocks. Bid-ask spreads, trading costs and the price-impact of trading are likely to increase with the decrease of trading volume. In all, these assumptions transform the pairs trading portfolio return into a strategy return that shares some of the features of an industry-wide return to pairs trading. Third, to capture the effect of illiquid stocks in the pairs-trading portfolios, we also consider a strategy where infrequently traded stocks, i.e., those without a full price history, are allowed to be selected for the pairs. Also, we capture the potential impact of transaction costs by selecting only pairs from the top-third most expensive stocks to trade, based on Proportional Effective Spread

[2]The results when using the 10-day closing period are practically similar to those implied by the strategy of unrestricted trading within the investment period, and are not reported for brevity.

(PESPR). PESPR is defined as the bid-ask spread over the price, see Chordia et al. (2000), Engelberg et al. (2009).

To summarize, we have four different pairs-trading strategies. The first one is the original selection of Gatev et al., with a constant number of 20 traded pairs. The second one is modified to have a long-bias in the S&P 500, but with the same number of 20 traded pairs. The third one has a flexible number of pairs, depending on the market volume, as explained above, but a with a maximum of 200 eligible pairs to choose from. The fourth one is the strategy that is geared towards stocks that are less frequently traded and have higher spreads, by selecting from the top-200 pairs with highest PESPR and including stocks with an incomplete price history. Table 5 shows the descriptive statistics of the momentum strategy and the four pairs-trading strategies.

[INSERT Table 5 HERE]

In order to analyze these dynamic trading strategies as a potential source of time variations in the market exposure of hedge fund returns, induced by changes in market illiquidity, we look at whether hedge fund returns load significantly on them. Results are presented in Table 6, which reports the number and average size of significant loadings of hedge funds on the dynamic strategy return.

[INSERT Table 6 HERE]

The momentum strategy, as well as the original pairs trading strategy proposed by Gatev et al. (2006), appear to be significant only for less than 15% of all funds in our sample. However, around 60% of the funds load significantly on the three modified pairs trading strategies, while about 24% load positively, but insignificantly. Only 4% have a negative and significant loading on pairs trading. Thus, our pairs trading return seems to capture a systematic element in the variation of hedge fund returns. This is not surprising, given that the motivation and implementation of the pairs trading strategy is mimicking industry practice, albeit in a stylized and non-sophisticated way, see Gatev et al. (2006). We therefore use the two pairs-trading strategies that allow for a flexible number of traded pairs in our subsequent analysis. The modified strategy that uses a fixed number of pairs for trading yields similar results that we do not report for brevity.

To see whether the liquidity effect found above is related to pairs trading, we now use the pairs trading return to sort hedge funds into portfolios. The first portfolio consists of hedge funds that load positively and significantly on the pairs trading return. The second portfolio consists of hedge funds that have an insignificant, but positive loading on the pairs trading return. The third portfolio consists of hedge funds that have no significant loading on pairs trading. We then regress each portfolio on the market return and the interaction term of market times illiquidity, controlling for the other risk factors, as in Table 2. Table 7 has the results for the pairs-trading strategy "PT-flexible", Table 8 for the strategy "PT-illiquid". Only the coefficients for the market return and the interaction term are shown.

[INSERT Table 7 HERE]

[INSERT Table 8 HERE]

The "All funds" columns of Table 7 show the familiar result of a switch in the loading on the interaction term: positive before 2003 and negative after. The same result is found in the columns "PT-exposed funds", with a slightly smaller (less positive) loading before 2003, but more negative after the break. For the non PT-exposed funds, however, we see a striking deviation from earlier results: there is no positive loading on the interaction term before the break, and a non-significant negative loading after the break. For the funds with negative PT-exposure, only the negative loadings after the break are significant. Thus, sorting on pairs-trading exposure selects funds that do, and do not exhibit a switching behavior with respect to the interaction term of market and illiquidity.

The results in Table 8 are based on exposure to a pairs-trading strategy that is explicitly skewed towards less liquid stocks to capture a possible liquidity effect caused by the selection of stocks. The result are qualitatively the same as in Table 8: the portfolio with PT-exposed funds are very similar to the All-funds portfolio, but the portfolio with non PT-exposed funds does not show the significant switch over the 2003 breakpoint.

The same holds for the portfolio with funds that have a negative PT-exposure.

With respect to both Table 7 and 8, we see a clear evidence of liquidity timing ability for the post-2003 period. I.e., the loading on the interaction term of the market return times ILLIQ is negative, so that market exposure of hedge funds is lower in times of higher market illiquidity. This suggest that the findings of Cao et al. (2009), who find evidence for this form of liquidity timing, are only valid for the most recent period.

5 How unique is 2003?

Motivated by the introduction of Autoquote on NYSE in 2003 and the dramatic improvement in liquidity that followed we have split our sample in June 2003. However, we want to test the sensitivity of our results to the exact date of the breakpoint.

In order to test for fund-specific breakpoints, we perform a changepoint regression on individual funds, as in Bollen and Whaley (2009) and Patton and Ramadorai (2010). It starts from a a general model for individual hedge fund returns with time-varying exposures, as in

$$R_{it} = \alpha_i + \beta_{it} r_{m,t} + \sum_k \gamma_{i,k} F_{t,k} + \varepsilon_{it}, \tag{7}$$

where R_{it} is the return of hedge fund i in month t, $r_{m,t}$ the return on the market and $F_{t,k}$ are the returns on the 7-factor model of Fung and Hsieh (2004). The time-variation in β_{it} is specified as

$$\beta_{it} = b_{i0} + b_{i0}^* \cdot 1_{\{t>\tau_i\}} + b_{i1} \cdot ILLIQ_{m,t} + b_{i1}^* \cdot ILLIQ_{m,t} \cdot 1_{\{t>\tau_i\}}, \tag{8}$$

where $1_{\{A\}}$ is the indicator function for event A and τ_i is the change-point for fund i.

We can combine equations (7) and (8) into one regression as

$$\begin{aligned} R_{it} = \alpha_i &+ \left(b_{i0} + b_{i0}^* \cdot 1_{\{t>\tau_i\}}\right) \cdot r_{m,t} \\ &+ \left(b_{i1} + b_{i1}^* \cdot 1_{\{t>\tau_i\}}\right) \cdot ILLIQ_{m,t} \cdot r_{m,t} \\ &+ \sum_k \gamma_{i,k} F_{t,k} + \varepsilon_{it}. \end{aligned} \tag{9}$$

For every fund, the model in Equation (9) is estimated for every change-point τ_i. The optimal change-point τ_i^* is the one that minimizes the sum of squared errors over all candidate change-points. Since the model is estimated for every change-point, we cannot use standard coefficient tests. Therefore, we test for significance by using a bootstrap procedure, see Patton and Ramadorai (2010) and Bollen and Whaley (2009). It is a two-stage procedure that consists first in estimating a constant parameter model under the null of no significant change-point, i.e., a constant parameter model with $b_{i0}^* = b_{i1}^* = 0$. We then draw bootstrap samples of hedge fund returns by re-sampling the residuals and adding them to the fitted return estimates. In order to account for autocorrelation of returns, we follow Patton and Ramadorai (2010) and Politis and Romano (1994) in that we draw the residuals in blocks of random size and starting point. The block lengths are drawn from a geometric distribution. In the second stage, we estimate an optimal change-point regression on each bootstrap sample. For each candidate changepoint we compute the F-statistic of Andrews et al. (1996):

$$F(\tau_i) = \frac{[SSE^* - SSE(\tau_i)](T - 2\nu)}{SSE(\tau_i)\,\nu} \tag{10}$$

where SSE^* is the sum of squared errors of the estimated constant parameter model, $SSE(\tau_i)$ corresponds to the change-point regression for time τ_i, and ν equals the number of factors in the change-point regression plus one. The significance of a change-point τ_i is determined by the test statistic $\bar{F}$:

$$\bar{F} = \sum_{\tau_i} F(\tau_i)\, w(\tau_i), \tag{11}$$

computed for equal weights $w(\tau_i)$. We consider a change-point parameter shift to be significant for a fund i if its $\bar{F}_i$ statistic exceeds the 90^{th} percentile of the distribution of the $\bar{F}$ statistic.

The funds for which we find a significant changepoint are graphically depicted in Figure 2. The Figure shows the largest peak of significant change-points around the year 2000. Moreover, the peaks of the change-points correspond to market-wide events as the LTCM-crisis of September 1998, the stock market crash in 2000 and the credit crisis of 2007/2008. This confirms the intuition that market-wide events have an impact on the systematic exposure of hedge funds. Bollen and Whaley (2009) also suggest that the peak in changepoints around 2000 is related to the end of the internet bubble. The one peak in Figure 2 that is not associated with a crisis or stock market decline is the year 2003, which we in this paper associate with the introduction of automated trading on the NYSE.

[INSERT Figure 2 HERE]

To test for the sensitivity of our results to the exact date of June 2003 for splitting the sample, however, we need to use a different method than changepoint regressions. The changepoint regressions assume that the loadings on the other risk factors are stable. If they are not, the coefficient estimates are likely to be biased. So, to verify whether the break is in the direction of our findings for the two subperiods, we perform a test whereby we vary the month of the breakpoint and measure the coefficient on the interaction term of the market return times illiquidity. Since it allows all loadings to change over the breakpoint, it better captures the change in loading on the interaction term. Figure 3 has the results, for the three different stock indices: Large, Mid and SmallCap. The underlying regression is that of Table 2, with a portfolio of hedge funds as the dependent variable and the lagged market return is included as a control.

[INSERT Figure 3 here]

The values of the T-statistics in Figure 3 reach the critical 95% significance level at different dates, depending on the type of index and whether we consider the positive coefficient before and negative coefficient after the breakpoint. Panel A shows that the positive coefficient before the breakpoint turns significant around mid-2003 for all markets. The significance for break points after 2003 corresponds to the results in Table 2, where the coefficient estimate is positive and significant for the whole sample as well as the first subperiod.

Panel B of Figure 3 shows how the negative coefficient after the breakpoint is significant for breakpoints after 2001 for the S&P 500 and S&P 400. For the S&P 600 SmallCap the coefficient turns significant after end-1999. For the most early breakpoints the coefficient is positive and significant, corresponding to the positive coefficient for the whole sample in Table 2.

The fact that significance in Panel A is found only after 2003, and in Panel B before 2001 could indicate that the positive and significant coefficients of Panel A and Table 2 are measuring a weaker effect, for which a longer data series is necessary. On the other hand, we should take into account that over the breakpoint date, all exposures are allowed to change, including the loading on the market index itself.

[INSERT Figure 4 here]

The difference between the Small Cap and the other markets disappear if we restrict the sample to funds that load significantly on the PT-illiquid strategy. Figure 4 shows the evolution of t-statistics over breakpoint dates when we restrict funds to only those that load on PT-illiquid, as in Table 8. In the figure, the lines for the respective markets are much closer together than in Figure 3. This is a result of the narrower selection of fund, filtering out funds that, according to Table 8, display no switching behavior in the interaction term of the market and illiquidity. In all, both Figures 3 and Figure 4 confirm a significant structural shift in parameters for the dynamic loading of hedge funds on the stock market around 2003, caused by market liquidity.

6 Conclusion

In this paper we document a shift in systematic stock market exposure of hedge funds, possibly caused by the dramatic improvement of liquidity in 2003. We find a distinctly different pattern of market risk and illiquidity before and after 2003, with illiquidity measured by Amihud's (2002) measure of stock market illiquidity. Before the breakpoint, hedge fund betas are positively related to ILLIQ, while afterwards they are negatively related. When Hendershott and Riordan (2009) observe that the introduction of Autoquote (automated trading) on NYSE in 2003 has changed the market structure by opening it up for algorithmic trading, our results are suggestive of an effect on the relation between market exposures of hedge funds and market liquidity.

One interpretation of our findings is that, before 2003, hedge funds acted as suppliers of liquidity, having a higher market exposure when stocks are undervalued due to low liquidity. This explains the positive coefficient on an interaction term of the market return times illiquidity. The reversal after 2003 points to a fundamental shift in how hedge funds interact with the stock market. The higher level of overall liquidity and the surge in automated trading have led to a liquidity timing behavior that was not possible, or too expensive, before that time. This is supported by the fact that funds with no exposure to pairs-trading return show no switch at all. This suggests an explanation rooted in sophisticated dynamic strategies used by hedge funds, of which the pairs trading strategies mimicked in this paper can only bear a rough resemblance.

References

Acharya, V. and L. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77*(2), 375–410.

Agarwal, V. and N. Naik (2004). Risks and portfolio decisions involving hedge funds. *Review of Financial Studies 17*(1), 63–98.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Amvella, S., I. Meier, and N. Papageorgiou (2010). Persistence analysis of hedge fund returns. Working paper, HEC Montréal.

Andrews, D., I. Lee, and W. Ploberger (1996). Optimal changepoint tests for normal linear regression. *Journal of Econometrics 70*(1), 9–38.

Aragon, G. and P. Strahan (2010). Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. Working Paper.

Asness, C., R. Krail, and J. Liew (2001). Do hedge funds hedge? *Journal of Portfolio Management 28*(1), 6–19.

Ben-David, I., F. Franzoni, and R. Moussawi (2010). The Behavior of Hedge Funds during Liquidity Crises. Working paper, Ohio State University.

Blitz, D., J. Huij, and M. Martens (2011). Residual Momentum. forthcoming.

Bollen, N. and V. Pool (2009). Do hedge fund managers misreport returns? Evidence from the pooled distribution. *The Journal of Finance 64*(5), 2257–2288.

Bollen, N. and R. Whaley (2009). Hedge Fund Risk Dynamics: Implications for Performance Appraisal. *The Journal of Finance 64*(2), 985–1035.

Brophy, D., P. Ouimet, and C. Sialm (2009). Hedge Funds as Investors of Last Resort? *Review of Financial Studies 22*(2), 541.

Brown, S., W. Goetzmann, and J. Park (1998). Hedge funds and the asian currency crisis of 1997.

Brown, S., W. Goetzmann, and J. Park (2000). Hedge funds and the Asian currency crisis. *The Journal of Portfolio Management 26*(4), 95–101.

Brunnermeier, M. and S. Nagel (2004). Hedge Funds and the Technology Bubble. *The Journal of Finance 59*(5), 2013–2040.

Brunnermeier, M. and L. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Cao, C., Y. Chen, B. Liang, and A. Lo (2009). Can Hedge Funds Time Market Liquidity? working paper.

Chordia, T., R. Roll, and A. Subrahmanyam (2000). Commonality in liquidity* 1. *Journal of Financial Economics 56*(1), 3–28.

De Jong, F. and J. Driessen (2006). Liquidity risk premia in corporate bond markets. mimeo.

Engelberg, J., P. Gao, and R. Jagannathan (2009). An anatomy of pairs trading: the role of idiosyncratic news, common information and liquidity. Working paper. Electronic copy available at: http://ssrn.com/abstract=1330689.

Fung, W. and D. Hsieh (1997). Empirical characteristics of dynamic trading strategies: the case of hedge funds. *Review of Financial Studies 10*(2), 275–302.

Fung, W. and D. Hsieh (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies 14*(2), 313–341.

Fung, W. and D. Hsieh (2002). Hedge-Fund Benchmarks: Information Content and Biases. *Financial Analysts Journal 58*(1), 22–34.

Fung, W. and D. Hsieh (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal 60*(5), 65–80.

Gatev, E., W. Goetzmann, and K. Rouwenhorst (2006). Pairs trading: Performance of a relative-value arbitrage rule. *Review of Financial Studies 19*(3), 797.

Getmansky, M., A. Lo, and I. Makarov (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics 74*(3), 529–609.

Goyenko, R., C. Holden, and C. Trzcinka (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics 92*(2), 153–181.

Hasbrouck, J. (2009). Trading costs and returns for US equities: Estimating effective costs from daily data. *The Journal of Finance 64*(3), 1445–1477.

Hendershott, T., C. Jones, and A. Menkveld (2011). Does Algorithmic Trading Improve Liquidity? forthcoming, Journal of Finance.

Hendershott, T. and R. Riordan (2009). Algorithmic trading and information. Working paper, NYU.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance 48*(1), 65–91.

Jylha, P., K. Rinne, and M. Suominen (2010). Do Hedge Funds Supply or Demand Liquidity? working paper, Aalto University.

Khandani, A. and A. Lo (2007). What happened to the quants in august 2007? *Journal of Investment Management 5*(4), 29–78.

Korajczyk, R. and R. Sadka (2004). Are momentum profits robust to trading costs? *Journal of Finance 59*(3), 1039–1082.

Korajczyk, R. and R. Sadka (2008). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics 87*(1), 45–72.

Liang, B. (2000). Hedge Funds: The Living and the Dead. *Journal of Financial and Quantitative Analysis 35*(3), 309–326.

Mitchell, M. and T. Pulvino (2001). Characteristics of Risk and Return in Risk Arbitrage. *The Journal of Finance 56*(6), 2135–2175.

Pastor, L. and R. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political economy 111*(3), 642–685.

Patton, A. (2009). Are "Market Neutral" Hedge Funds Really Market Neutral? *Review of Financial Studies 22*(7), 2295–2330.

Patton, A. and T. Ramadorai (2010). On the Dynamics of Hedge Fund Risk Exposures. working paper.

Politis, D. and J. Romano (1994). The Stationary Bootstrap. *Journal of the American Statistical Association 89*(428), 1303–1313.

Posthuma, N. and P. Sluis (2003). A Reality Check on Hedge Funds Returns. Working paper, VU University Amsterdam.

Sadka, R. (2009). Liquidity Risk and the Cross-Section of Expected Hedge-Fund Returns. Working paper.

Appendix A: The pairs trading algorithm

The algorithm for constructing a pairs trading strategy follows the setup of Gatev et al. (2006). At the beginning of each calendar month we start by identifying the pairs eligible for trading over the following 6-month trading period. The pairs formation period is 12 months prior to the trading period. We filter out stocks that do not trade continuously over the whole 12 month period to ensure relatively liquid stocks being traded. (This selection is relaxed for a specific variant of the pairs-trading return, PT-illiquid for which we want to capture exposure to less liquid stocks.) For each stock i a normalized price series P_{it}, with $P_{i0} \equiv 1$ is constructed, where t=0 is the start of the formation period. For a given month m, the selection criterion for a 'pair' is the sum of squared differences between the two normalized price series:

$$D_{i,j,m} = \sum_{t=1}^{\tau_m} (P_{i,t} - P_{j,t})^2 , \tag{A1}$$

where τ_m is the number of trading days in the 12-month formation period prior to month m. Each month, the top N pairs are selected that have the smallest distance measure during the pairs formation period.[3] They form the pool of eligible pairs for trading in the following 6 months.

During the trading period, the price-difference of the eligible pairs are observed on a daily basis. Once a pair has diverged by more than two standard deviations, the lower-priced stock is bought and the higher-priced stock is sold (short). The transaction is assumed to take place one day after divergence to mitigate any market microstructure effects. The positions are closed once the prices of the pair have converged or at the end of the 6-month trading period, whichever comes first. We also apply an alternative rule of unwinding a position after convergence or up to a maximum of 10 days, following Engelberg et al. (2009). Note that a position in a pair can be opened an closed several times during the trading period. As well, some eligible pairs never trade due to lack of divergence over the 6-month period.

For each pair P traded on day t the buy-and-hold return $r_{P,t}$ is defined as

$$r_{P,t} = \frac{\sum\limits_{i \in P} w_{i,t} r_{i,t}}{\sum\limits_{i \in P} w_{i,t}} , \tag{A2}$$

where r_i denotes the return on security i of pair P and the weights w_i are given by

$$w_{i,t} = (1 + r_{i,1}) \dots (1 + r_{i,t-1}) . \tag{A3}$$

[3] We choose $N = 20$ for the pairs-trading strategy that replicates the methodology of Gatev et al. (2006).

The return on the portfolio of pairs is calculated as the return on invested capital, giving equal weights on all pairs selected for trading. Daily returns are compounded in order to obtain monthly returns. At the start of each month m a new pairs-trading strategy is started, so that we obtain a series of six overlapping portfolio returns on strategies, each starting one month apart. The pairs-trading strategy return is the monthly average of the six running portfolio returns.

Table 1: Summary statistics of fund and market index returns

This table presents descriptive statistics on monthly fund and market index returns over the sample period January 1994 to April 2009. The columns headed "median fund" present the medians of the statistics in the rows across the funds in each style category with at least twelve observations. The penultimate row gives the median number of time series observations.

	Median fund						
	Equity Market Neutral	Long/Short Equity	Event Driven	Convertible Arbitrage	S&P 500	S&P 400	S&P 600
Mean	0.34	0.61	0.63	0.51	0.63	0.85	0.84
Median	0.34	0.61	0.63	0.51	0.63	0.70	0.67
Standard deviation	2.03	3.49	2.14	1.68	4.48	5.07	5.41
Skewness	-0.28	-0.19	-0.54	-0.51	-0.75	-0.77	-0.66
Kurtosis	4.24	4.29	5.80	5.30	4.13	5.31	4.56
Minimum	-5.36	-9.10	-6.53	-5.05	-16.80	-21.58	-20.19
Maximum	4.70	9.11	5.70	4.64	9.78	14.95	17.53
Jarque-Bera statistic	6.66	7.58	30.64	23.62	27.46	59.63	32.47
Jarque-Bera p-value	0.02	0.02	0.00	0.00	0.00	0.00	0.00
Autocorr. lag 1	0.14	0.14	0.25	0.40	0.12	0.18	0.13
Autocorr. lag 2	0.04	0.06	0.11	0.12	-0.03	-0.12	-0.10
Number of obs.	46	51	59	65	186	186	186
Total number of obs.	607	3432	743	255	-	-	-

Table 2: Portfolio regression with Equity Market Neutral and Long/Short Equity funds

This table reports the outcomes of six separate time-series regressions. The dependent variable is the return on the value-weighted portfolio of funds with Long/Short Equity Hedge (LSE) and Equity Market Neutral (EMN) style descriptors. Per subperiod, the regression is estimated seperately for ILLIQ and PS as measures of liquidity. ILLIQ is the Amihud (2002) illiquidity measure, PS is the Pastor-Stambaugh (2002) measure of liquidity, mkt is the return on the value-weighted CRSP return, mkt*L is the interaction term of the market return with the (il)liquidity measure, VIX is the CBOE implied volatility index, mkt t-1, mkt t-2 are the one and two-month lagged market returns, smb is the Fama-French small-minus-big factor, yldchange is the change in the term spread, def is default spread, ptfsbd, ptfsfx and ptfscom are the bond, currency and commodity timing factors from Fung and Hsieh (2004) as provided by David Hsieh on his website, ΔL is the innovations in the corresponding liquidity factor. Newey-West t-statistics between parentheses and *, **, *** denote significance at the 10%, 5% and 1%-level, respectively.

	mkt	mkt × L	mkt × VIX	mkt t-1	mkt t-2	smb	yldchg	def	ptfsbd	ptfsfx	ptfscom	ΔL	R^2
Panel A: whole period													
Liq PS	0.48***	0.00	0.00	0.04	0.11***	0.27***	−0.63	1.31	−0.35	−0.17	0.41	2.30*	0.76
	(6.30)	(−0.01)	(−0.95)	(1.55)	(4.19)	(5.08)	(−1.37)	(1.20)	(−0.41)	(−0.41)	(0.52)	(1.70)	
ILLIQ	0.36***	0.26**	0.00**	0.02	0.11***	0.25***	−0.68	−0.06	−0.25	−0.14	0.50	−2.74*	0.77
	(4.88)	(2.31)	(−2.36)	(1.04)	(4.58)	(4.33)	(−1.60)	(−0.06)	(−0.33)	(−0.41)	(0.62)	(−1.82)	
Panel B: 1994 - 2003													
Liq PS	0.48***	0.87**	0.00	0.02	0.12***	0.32***	−0.01	3.44***	−1.15	0.05	0.76	−0.35	0.83
	(5.11)	(2.46)	(−0.34)	(1.07)	(4.86)	(7.34)	(−0.02)	(2.80)	(−1.35)	(0.11)	(0.89)	(−0.21)	
ILLIQ	0.26***	0.48***	−0.01**	0.04*	0.12***	0.30***	−0.06	2.05	−0.50	0.06	0.45	−1.47	0.83
	(2.73)	(3.40)	(−2.32)	(1.86)	(4.53)	(5.77)	(−0.09)	(1.34)	(−0.58)	(0.13)	(0.55)	(−1.03)	
Panel C: 2003 - 2008													
Liq PS	0.66***	−0.85	−0.01***	0.05	0.09***	0.02	−0.87	−1.32	0.48	−0.12	0.93	2.23	0.74
	(6.66)	(−1.48)	(−3.93)	(1.29)	(2.88)	(0.26)	(−1.34)	(−0.61)	(0.36)	(−0.16)	(0.96)	(1.02)	
ILLIQ	0.85***	−1.75**	0.00	0.01	0.15***	0.00	−0.79	−1.72	0.86	0.13	0.93	−22.35***	0.76
	(5.74)	(−2.00)	(−0.50)	(0.16)	(4.22)	(0.06)	(−1.31)	(−1.26)	(0.89)	(0.21)	(0.94)	(−3.19)	

Table 3: Portfolio regression with unsmoothed hedge fund returns

For hedge fund returns corrected for serial correlation, this table reports the outcomes of six separate time-series regressions. The dependent variable is the return on the value-weighted portfolio of funds with Long/Short Equity Hedge (LSE) and Equity Market Neutral (EMN) style descriptors. Per subperiod, the regression is estimated seperately for ILLIQ and PS as measures of liquidity. ILLIQ is the Amihud (2002) illiquidity measure, PS is the Pastor-Stambaugh (2002) measure of liquidity, mkt is the return on the value-weighted CRSP return, mkt*L is the interaction term of the market return with the (il)liquidity measure, VIX is the CBOE implied volatility index, mkt t-1, mkt t-2 are the one and two-month lagged market returns, smb is the Fama-French small-minus-big factor, yldchange is the change in the term spread, def is default spread, ptfsbd, ptfsfx and ptfscom are the bond, currency and commodity timing factors from Fung and Hsieh (2004) as provided by David Hsieh on his website, ΔL is the innovations in the corresponding liquidity factor. Newey-West t-statistics between parentheses and *, **, *** denote significance at the 10%, 5% and 1%-level, respectively.

	mkt	mkt × L	mkt × VIX	mkt t-1	mkt t-2	smb	yldchg	def	ptfsbd	ptfsfx	ptfscom	ΔL	R^2
Panel A: whole period													
Liq PS	0.57∗∗∗	−0.04	0.00	0.00	0.10∗∗∗	0.30∗∗∗	−0.75	1.09	−0.48	−0.20	0.63	3.28∗∗	0.76
	(6.57)	(−0.08)	(−1.21)	(−0.11)	(3.54)	(5.10)	(−1.50)	(0.89)	(−0.52)	(−0.44)	(0.69)	(2.10)	
ILLIQ	0.47∗∗∗	0.22	−0.01∗∗	−0.02	0.10∗∗∗	0.27∗∗∗	−0.70	−0.16	−0.41	−0.16	0.71	−3.76∗∗	0.77
	(5.15)	(1.63)	(−2.46)	(−0.69)	(3.91)	(4.29)	(−1.44)	(−0.14)	(−0.49)	(−0.42)	(0.76)	(−2.20)	
Panel B: 1994 - 2003													
Liq PS	0.55∗∗∗	0.93∗∗	0.00	−0.01	0.11∗∗∗	0.35∗∗∗	−0.06	3.50∗∗∗	−1.24	0.00	0.90	0.21	0.83
	(5.31)	(2.32)	(−0.45)	(−0.46)	(4.33)	(7.47)	(−0.09)	(2.72)	(−1.33)	(0.00)	(0.97)	(0.11)	
ILLIQ	0.30∗∗∗	0.52∗∗∗	−0.01∗∗	0.00	0.11∗∗∗	0.33∗∗∗	−0.07	1.99	−0.52	0.01	0.58	−2.23	0.84
	(3.08)	(3.49)	(−2.48)	(0.07)	(4.09)	(5.81)	(−0.10)	(1.24)	(−0.56)	(0.03)	(0.65)	(−1.42)	
Panel C: 2003 - 2008													
Liq PS	0.81∗∗∗	−0.99	−0.01∗∗∗	0.02	0.07∗∗	0.01	−0.90	−1.24	0.26	−0.16	1.34	3.37	0.73
	(6.70)	(−1.33)	(−3.76)	(0.41)	(2.12)	(0.08)	(−1.09)	(−0.48)	(0.17)	(−0.18)	(1.15)	(1.27)	
ILLIQ	1.08∗∗∗	−2.36∗∗	0.00	−0.04	0.15∗∗∗	−0.01	−0.77	−1.90	0.68	0.17	1.35	−26.19∗∗∗	0.75
	(6.19)	(−2.34)	(−0.33)	(−0.60)	(3.60)	(−0.10)	(−1.05)	(−1.14)	(0.61)	(0.24)	(1.11)	(−3.20)	

Table 4: Individual fund regressions

This table shows the cross-sectional statistics for the interaction term $R^m \times$ ILLIQ in the regressions of individual hedge fund returns on the hedge fund risk factors. For each column, funds are selected based on the exposure the index. The market return and ILLIQ measure are computed for each index separately. The regressions include the hedge funds risk factors, as in Table 2. The cross-sectional t-statistic is the t-statistic for the test on whether the average estimate of the individual regressions is different from zero. The fraction of funds with significant positive or negative loadings uses the 5% significance level.

	All funds	S&P 500	S&P 400	S&P 600
Panel A: 1996 - 2009				
Mean coefficient	−0.40	−0.13	−0.46	−0.78
Mean t-statistic	−0.47	−0.19	−0.67	−0.69
Cross-sectional t-statistic	−3.92	−0.82	−2.34	−5.67
Fraction of significant positive coefficients	0.09	0.11	0.08	0.07
Fraction of significant negative coefficients	0.20	0.15	0.25	0.24
Panel B: 1996 - 2003				
Mean coefficient	0.23	0.30	0.16	0.13
Mean t-statistic	0.25	0.39	0.12	0.07
Cross-sectional t-statistic	2.24	1.82	0.82	1.21
Fraction of significant positive coefficients	0.16	0.18	0.14	0.11
Fraction of significant negative coefficients	0.09	0.08	0.11	0.08
Panel C: 2003 - 2009				
Mean coefficient	−0.71	−0.52	−0.85	−0.80
Mean t-statistic	−0.77	−0.75	−0.90	−0.58
Cross-sectional t-statistic	−3.29	−1.16	−3.13	−2.56
Fraction of significant positive coefficients	0.06	0.06	0.06	0.07
Fraction of significant negative coefficients	0.24	0.23	0.26	0.24

Table 5: Performance of the dynamic strategies

Descriptive statistics of monthly excess returns to the dynamic strategies for the period January 1994 to April 2009. “MOM-FF” is the return to momentum, i.e., the return on the long portfolio of past 12-month winning stocks minus the return on the past 12-month losing stocks, as provided by Kenneth French on his website. “PT-original” is the pairs trading strategy from Gatev et al. (2006), exploiting temporary deviations in the stock price-paths of the top-20 of matching pairs of stock. “PT-modified” is a modification whereby the funds not invested in pairs are assumed to be invested in the S&P 500 index future. “PT-flexible” is a modification where we take the total hedge fund industry size as starting assets and restrict pairs trading to a maximum of 40% of the dollar volume of each stock, with total pairs trading volume a maximum of 5% of the total market dollar volume at the end of each month. There is no restriction on the number of traded pairs. The remaining assets not invested in pairs trading are invested in the S&P 500. ”PT-illiquid” is the strategy where stocks with an incomplete price history are allowed and those with high effective spreads are selected. It restricts pairs trading to a maximum of 40% of the dollar volume of each stock, with total pairs trading volume a maximum of 1% of the total market dollar volume at the end of each month. Stocks considered for the pairs trading are all from the NYSE-Amex universe as provided in the CRSP daily stock file.

	MOM-FF	PT-original	PT-modified	PT-more pairs	PT-illiquid
mean	0.58	0.13	0.330	0.28	0.36
median	0.79	0.14	0.493	0.43	1.05
stdev	5.98	0.42	1.796	1.61	3.85
skew	-1.54	0.29	-0.873	-1.14	-0.93
kurt	11.37	4.12	6.143	7.28	5.79
min	-34.75	-1.04	-6.988	-7.56	-18.46
max	18.39	1.54	6.360	5.24	10.80
Lag 1 autocorr.	0.07	0.05	0.228	0.20	0.20
Lag 2 autocorr.	-0.10	-0.12	-0.044	-0.01	-0.05

Table 6: Hedge fund loadings on the dynamic strategies

This table reports summary statistics of regression outcomes of individual hedge funds on the dynamic strategies. See Table 5 and the text for the description of the strategies. Significance is based on 5%-significance.

	MOM-FF	PT-original	PT-modified	PT-flexible	PT-illiquid
Average loading	-0.01	1.00	1.06	1.31	1.09
Average t-stat	-0.06	0.65	3.04	2.99	2.91
Significantly positive loadings					
Fraction	0.13	0.15	0.62	0.60	0.61
Beta coefficient	0.33	3.52	1.66	2.10	1.69
Average t-stat	3.71	2.63	4.88	4.96	4.77
Significantly negative loadings					
Fraction	0.18	0.03	0.04	0.04	0.04
Beta coefficient	-0.32	-3.27	-0.95	-1.20	-1.01
Average t-stat	-3.25	-2.82	-3.67	-3.85	-3.91
Insignificant positive loadings					
Fraction	0.38	0.56	0.23	0.24	0.24
Beta coefficient	0.11	1.52	0.42	0.60	0.57
Average t-stat	0.90	0.92	1.10	1.14	1.13
Insignificant negative loadings					
Fraction	0.31	0.27	0.11	0.11	0.12
Beta coefficient	-0.12	-1.10	-0.24	-0.32	-0.24
Average t-stat	-0.88	-0.71	-0.79	-0.81	-0.81

Table 7: Regression results for portfolio sorts on modified pairs-trading exposure

This table reports the outcome of a time-series regression. Dependent variable is the return on the value-weighted portfolio of funds sorted on exposure to the pairs trading return "PT-flexible". "All funds" is the portfolio with hedge funds with styles Long/Short Equity (LSE) and Equity Market Neutral (EMN). "PT-exposed funds" is the subset of the all-funds portfolio that includes only funds which have a significant positive loading on the return to the pairs trading strategy, "non PT-exposed" is the portfolio with the funds with insignificant positive exposure and 'negative PT-exposure' is for funds with negative exposure to the pair-trading return. R^m is the market return, $R^m \times$ ILLIQ is the interaction term of the market return with Amihud's illiquidity measure. Included, but not reported are the hedge fund risk factors as in Table 2. T-statistics are between parentheses, based on heteroskedasticity and autocorrelation-corrected standard errors. *, **, *** denote significance at the 10%, 5% and 1%-level, respectively.

	All funds		PT-exposed funds		non PT-exposed		negative PT-exposure	
	R^m	$R^m \times$ ILLIQ	R^m	$R^m \times$ ILLIQ	R^m	$R^m \times$ ILLIQ	R^m	$R^m \times$ ILLIQ
Panel A: 1996 - 2009								
S&P 500	0.11	0.69***	0.29***	0.62***	0.18***	−0.28**	−0.17**	0.02
	(1.35)	(3.66)	(3.03)	(2.83)	(3.60)	(−2.27)	(−2.19)	(0.08)
S&P 400 MidCap	0.13**	0.54***	0.29***	0.51***	0.15***	−0.14	−0.06	−0.09
	(2.06)	(3.95)	(4.14)	(3.48)	(3.66)	(−1.56)	(−0.71)	(−0.56)
S&P 600 SmallCap	0.07	0.46***	0.19***	0.47***	0.11***	−0.07	−0.04	−0.12
	(1.20)	(5.27)	(3.01)	(4.79)	(2.90)	(−1.03)	(−0.58)	(−1.02)
Panel B: 1996 - 2003								
S&P 500	0.03	0.88***	0.25*	0.73**	0.08	−0.07	−0.47***	0.63
	(0.20)	(2.69)	(1.73)	(2.21)	(0.84)	(−0.34)	(−2.64)	(1.39)
S&P 400 MidCap	0.09	0.63***	0.27**	0.55**	0.05	0.02	−0.18	0.10
	(0.77)	(2.77)	(2.31)	(2.47)	(0.62)	(0.14)	(−1.32)	(0.43)
S&P 600 SmallCap	0.11	0.41**	0.27*	0.38*	0.07	−0.04	−0.09	−0.06
	(0.83)	(2.22)	(1.84)	(1.78)	(0.82)	(−0.30)	(−0.55)	(−0.28)
Panel C: 2003 - 2009								
S&P 500	0.93***	−3.38***	1.15***	−3.72***	0.45***	−1.45*	0.42***	−2.80***
	(5.71)	(−4.22)	(6.46)	(−4.24)	(2.71)	(−1.74)	(2.61)	(−3.56)
S&P 400 MidCap	0.74***	−2.22***	0.91***	−2.32***	0.40***	−1.01*	0.36***	−2.20***
	(5.94)	(−4.26)	(6.81)	(−4.15)	(3.09)	(−1.78)	(2.91)	(−4.32)
S&P 600 SmallCap	0.67***	−1.47***	0.86***	−1.65***	0.32***	−0.57	0.21**	−1.14***
	(6.04)	(−4.34)	(6.95)	(−4.36)	(2.70)	(−1.49)	(2.37)	(−4.34)

Table 8: Results for pairs trading with high-spread stocks

This table reports the outcome of a time-series regression. Dependent variable is the return on the value-weighted portfolio of funds sorted on exposure to the pairs trading return "PT-illiquid". This is the strategy where funds with an incomplete return history and the highest spreads are selected for the pairs. "All funds" is the portfolio with hedge funds with styles Long/Short Equity (LSE) and Equity Market Neutral (EMN). "PT-exposed funds" is the subset of the all-funds portfolio that includes only funds which have a significant positive loading on the return to the pairs trading strategy, "non PT-exposed" is the portfolio with the funds with insignificant positive exposure and 'negative PT-exposure' is for funds with negative exposure to the pair-trading return. R^m is the market return, $R^m\times$ ILLIQ is the interaction term of the market return with Amihud's illiquidity measure. Included, but not reported are the hedge fund risk factors as in Table 2. T-statistics are between parentheses, based on heteroskedasticity and autocorrelation-corrected standard errors. *, **, *** denote significance at the 10%, 5% and 1%-level, respectively.

	All funds		PT-exposed funds		non PT-exposed		negative PT-exposure	
	R^m	$R^m \times$ ILLIQ	R^m	$R^m \times$ ILLIQ	R^m	$R^m \times$ ILLIQ	R^m	$R^m \times$ ILLIQ
Panel A: 1996 - 2009								
S&P 500	0.11	0.69∗∗∗	0.27∗∗∗	0.64∗∗∗	0.13∗∗	−0.19	−0.21∗∗∗	0.26
	(1.35)	(3.66)	(3.05)	(2.92)	(2.50)	(−1.34)	(−3.34)	(1.36)
S&P 400 MidCap	0.13∗∗	0.54∗∗∗	0.26∗∗∗	0.56∗∗∗	0.10∗∗	−0.01	−0.12∗	0.13
	(2.06)	(3.95)	(3.59)	(3.18)	(1.99)	(−0.06)	(−1.72)	(0.80)
S&P 600 SmallCap	0.07	0.46∗∗∗	0.18∗∗∗	0.47∗∗∗	0.07∗	−0.02	−0.10	0.04
	(1.20)	(5.27)	(2.83)	(4.49)	(1.75)	(−0.32)	(−1.46)	(0.39)
Panel B: 1996 - 2003								
S&P 500	0.03	0.88∗∗∗	0.26∗	0.71∗∗	0.11	−0.14	−0.39∗∗∗	0.61∗
	(0.20)	(2.69)	(1.76)	(2.09)	(0.87)	(−0.50)	(−2.98)	(1.83)
S&P 400 MidCap	0.09	0.63∗∗∗	0.24∗∗	0.63∗∗	0.06	0.04	−0.20∗	0.26
	(0.77)	(2.77)	(1.97)	(2.50)	(0.55)	(0.19)	(−1.87)	(1.17)
S&P 600 SmallCap	0.11	0.41∗∗	0.27∗	0.37∗	0.13	−0.14	−0.14	0.10
	(0.83)	(2.22)	(1.90)	(1.74)	(1.15)	(−0.83)	(−1.22)	(0.56)
Panel C: 2003 - 2009								
S&P 500	0.93∗∗∗	−3.38∗∗∗	1.08∗∗∗	−3.36∗∗∗	0.45∗∗∗	−1.68∗∗	0.24∗∗	−1.95∗∗∗
	(5.71)	(−4.22)	(6.22)	(−3.97)	(2.79)	(−2.04)	(2.54)	(−4.26)
S&P 400 MidCap	0.74∗∗∗	−2.22∗∗∗	0.86∗∗∗	−2.04∗∗∗	0.39∗∗∗	−1.14∗∗	0.21∗∗∗	−1.58∗∗∗
	(5.94)	(−4.26)	(6.64)	(−3.69)	(3.19)	(−2.09)	(2.94)	(−5.42)
S&P 600 SmallCap	0.67∗∗∗	−1.47∗∗∗	0.81∗∗∗	−1.49∗∗∗	0.30∗∗	−0.61	0.11∗	−0.82∗∗∗
	(6.04)	(−4.34)	(6.69)	(−3.99)	(2.52)	(−1.60)	(1.82)	(−4.32)

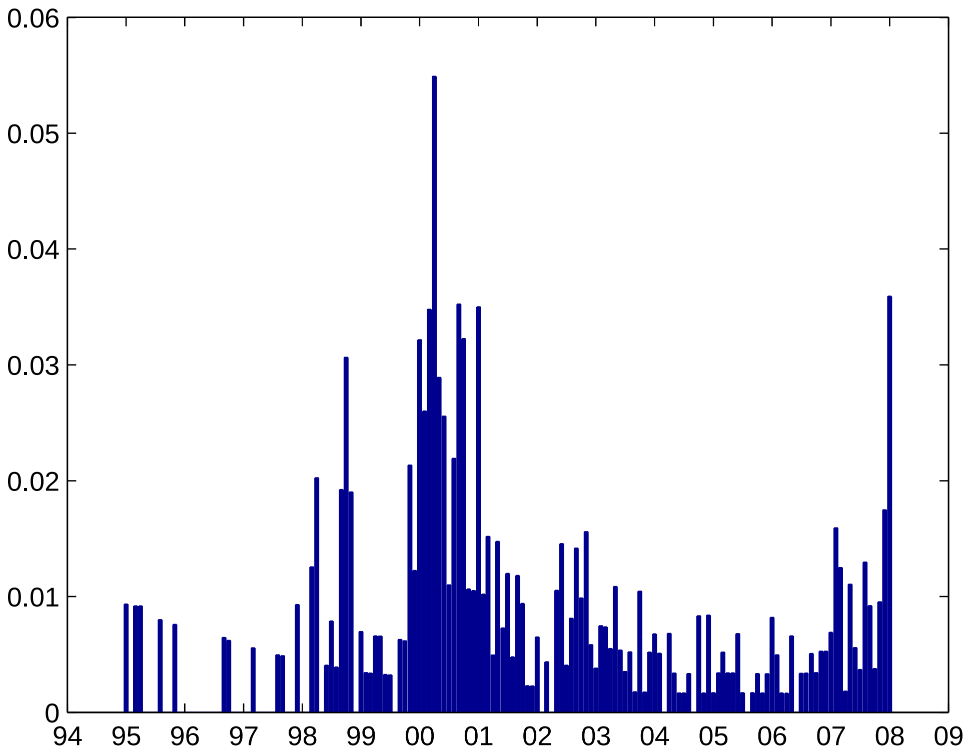
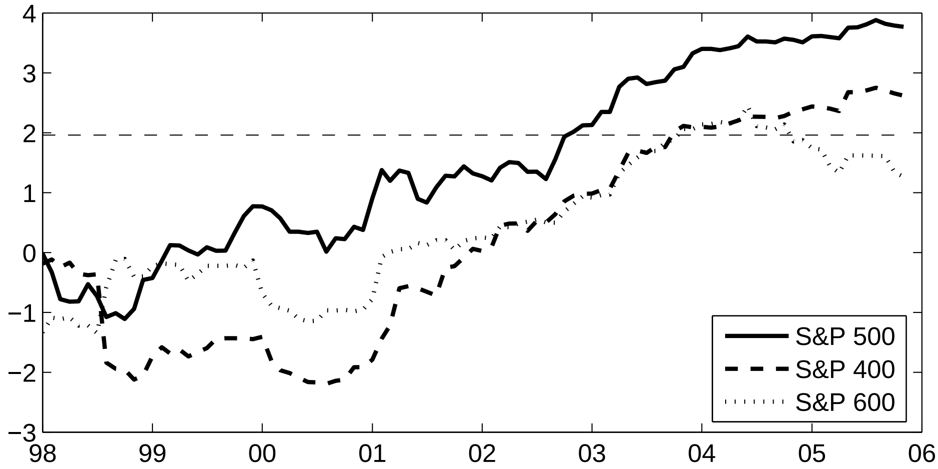
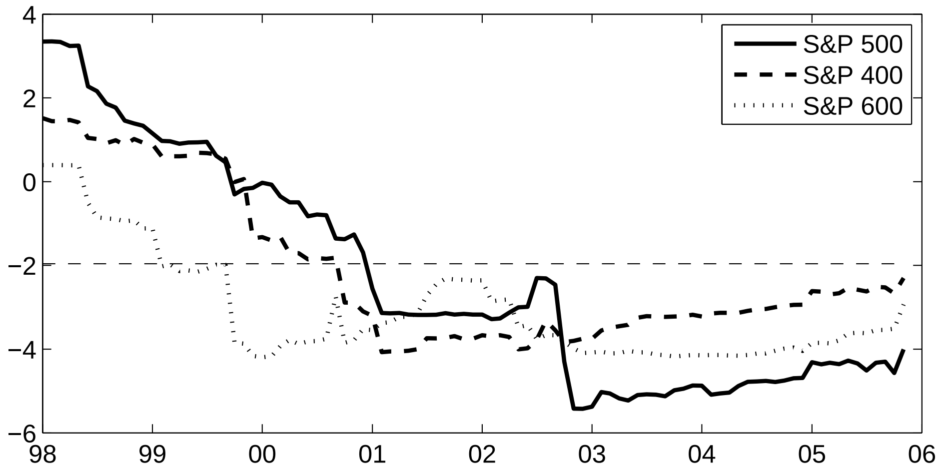


Figure 2: Significant changepoints

This graph shows the estimated change points (under 90% significance) with respect to the interaction term in the regression of the hedge fund return on the S&P 500. The funds are of the type Long/Short Equity (LSE) or Equity Market Neutral (EMN). The y-axis is the percentage of hedge funds with a significant changepoint over all candidate funds.



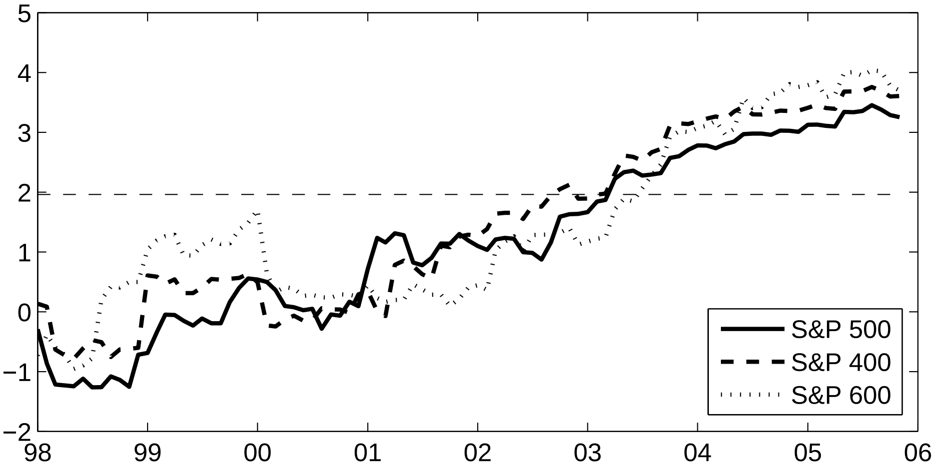
Panel A: Before breakpoint



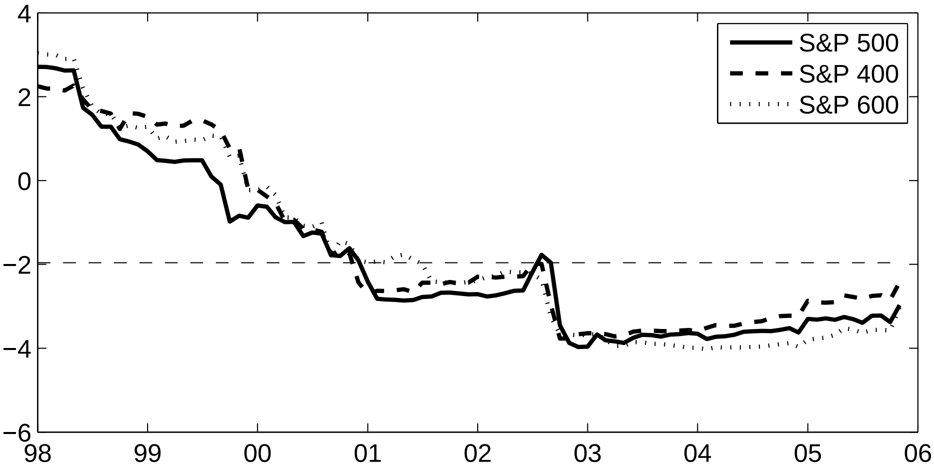
Panel B: After breakpoint

Figure 3: T-statistics before and after breakpoints

This graph shows the t-values for the interaction term of ILLIQ times the market for a given date that splits up the sample. Panel A has the t-values for the sample before the end date on the x-axis. Panel B has the t-values for the sample after the start date on the x-axis. The solid line represents the results for the portfolio of Long/Short Equity (LSE) and Equity Market Neutral (EMN) hedge funds that are associated with the S&P 500 as the market index, using the AIC selection criterion. In the same way, the dashed line is for the S&P 400 MidCap and the dotted line for the S&P 600 SmallCap index. The regression specification is identical to the one specified in Table 2, i.e. controlling for the usual risk factors, illiquid holdings with lagged S&P returns and volatility timing with the VIX index.



Panel A: Before breakpoint



Panel B: After breakpoint

Figure 4: T-statistics before and after breakpoints for PT-illiquid exposed funds

This graph shows the t-values for the interaction term of ILLIQ times the market for a given date that splits up the sample. Panel A has the t-values for the sample before the end date on the x-axis. Panel B has the t-values for the sample after the start date on the x-axis. The solid line represents the results for the portfolio of Long/Short Equity (LSE) and Equity Market Neutral (EMN) hedge funds that have a significant exposure to the pairs trading return "PT-illiquid", i.e. the strategy where funds with an incomplete return history and the highest spreads are selected for the pairs. The solid line corresponds to the S&P 500 as the market index, the dashed line - to the S&P 400 MidCap and the dotted line - to the S&P 600 SmallCap index. The regression specification is identical to the one specified in Table 2, i.e. controlling for the usual risk factors, illiquid holdings with lagged S&P returns and volatility timing with the VIX index.