Time Varying Market Efficiency

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Abstract

Market efficiency requires that arbitrageurs are able to raise the capital needed to arbitrage away mispricing in the cross-section of stock returns. We identify a set of capital constraints that impede the flow of funds to arbitrage strategies. When this flow is particularly curtailed, investors are unable to fully implement arbitrage strategies, allowing some level of inefficiency to persist. In turn, this leads to higher cross-sectional return predictability and stronger performance of arbitrage strategies in the future, as mispricing is eventually corrected. Thus, the degree of market efficiency is not a static concept but varies across time as arbitrage agents face time-varying constraints to arbitrage capital.
The seminal review of Fama (1970) defines market efficiency as a static concept, and the notion is often justified by arguing that if markets were inefficient, rational traders would arbitrage away any temporary mispricing. However, if capital markets are not perfect, price efficiency will not arise naturally, but only through the trading actions of rational arbitrageurs who require capital in order to return prices to fundamental value when they diverge from equilibrium. But if arbitrage capital is constrained (as is often the case in imperfect capital markets) market efficiency cannot be re-established instantaneously. Instead, stock prices will converge to fundamental value with a delay; this slow convergence process, in turn, implies ex-post predictability in the cross-section of stock returns.

In this paper, we explore the premise that capital constraints curtail the availability of arbitrage capital, which results in periods of aggregate inefficiencies in the cross-section of stock returns. If arbitrage capital is inadequate in any given time period, stock prices will not fully reflect fundamental values (resulting in temporary market inefficiencies) and return predictability will be higher over the following period.

We measure return predictability using the ex-post return performance of an actively managed traded strategy (AMTS) that is based on four cross-sectional anomalies documented in the literature, namely, momentum, profitability, reversals, and value. We measure arbitrage capital using flows to mutual funds whose trades mirror those of our actively managed strategy. Flows to these funds act as a proxy for the flows to arbitrage strategies where arbitrage capital is used to target market inefficiencies and move stock prices toward fundamental values when they diverge.

We first argue that the flow of capital to arbitrage strategies is itself affected by time varying capital constraints. When these constraints are binding, fund managers are unable to raise new capital
and in some cases must liquidate existing positions to meet the demand for redemptions. All else equal, we expect that periods of high constraints should be associated with lower flows to arbitrage funds. We examine the influence of two sources of capital constraints: market-wide, and performance-specific. Market-wide constraints result from liquidity shocks or from increases in borrowing costs or trading costs, all of which decreases investors’ propensity to invest in arbitrage equity strategies. Performance-specific constraints arise as a result of information asymmetry between investors and fund managers (Shleifer and Vishny, 1997). If investors mistrust managers’ ability to arbitrage away mispricing, a Stiglitz-Weiss (1981) type of credit rationing could arise in the market for arbitrage capital.

Next, we argue that as arbitrage capital varies through time, so does the degree of cross-sectional market efficiency. Periods marked by low arbitrage flows are periods during which markets are less efficient and stock prices are more likely to diverge from fundamental values. Any mispricing that is present at the beginning of such period will likely persist throughout the period. Thus, periods marked by low arbitrage flows will be followed by periods with higher cross-sectional return predictability, which will manifest in the form of higher returns to the actively managed trading strategy. Conversely, periods with high arbitrage flows will be followed by periods of lower cross-sectional return predictability which manifest in the form of lower returns to the actively managed trading strategy.

The preceding arguments suggest that we should observe relatively lower flows to arbitrage strategies when constraints on arbitrage capital are binding, and that these constrained flows should lead to periods of relatively higher return predictability in the future. Following these lines of thought, we formulate the following hypotheses:

H1: Flows to arbitrage funds are lower in the presence of performance-based as well as market-wide constraints on arbitrage capital.

H2: Returns to arbitrage strategies are higher following periods of lower flows to arbitrage funds.
We find empirical support for our hypotheses. First, both types of capital constraints impede flows to arbitrage funds. In turn, these lower arbitrage flows predict higher profitability of cross-sectional arbitrage strategies in the future. Our findings underscore the point that market efficiency is not a static concept, and that markets become efficient owing to intervention by economic agents. As the constraints on these agents vary over time, so does the degree of market efficiency.

Our paper is closely related to the growing literature on limits to arbitrage, pioneered by Shleifer and Vishny (1997). In their model, performance-sensitive investors redeem their funds when arbitrage strategies underperform, causing prices to move away from fundamental values. These types of performance-related constraints also arise from the models of He and Krishnamurthy (2012a; 2012b), where managers’ underperformance leads to capital rationing. Likewise, Pastor and Stambaugh (2010) develop a model where investors use past realized returns to infer the efficacy of active management, and allocate funds accordingly.² Vayanos (2004) shows that fund managers are unwilling to hold illiquid assets following poor performance, due to redemption risk, while Vayanos and Woolley (2011) show that investors rationally infer managers’ ability from performance and withdraw capital following underperformance by fund managers.


We make two important contributions to this literature. First, we find evidence supporting the notion that arbitrage capital is rationed following subpar performance of arbitrage strategies, and also in the presence of market-wide funding constraints that are unrelated to managers’ past performance.

² See Gromb and Vayanos (2010) for an extensive review of theoretical literature on limits of arbitrage.
Second, we provide a direct, inter-temporal empirical link between flows to arbitrage capital and the degree of market efficiency.

Our paper is also related to the literature documenting the effect of excess fund flows on asset prices. In particular, Coval and Stafford (2007) examine the cost of asset fire sales (purchases) and show that excess equity transactions cause significant price pressures that subsequently reverse. Similarly Anton and Polk (2010), Frazzini and Lamont (2008), Jotikasthira, Lundblad, and Ramadorai (2012), Greenwood and Thesmar (2011), and Lou (2012) show that excess fund flows have large price effects. In contrast to these studies we narrow our focus on flows to arbitrage strategies and show that the main effect of arbitrage flows is to prevent mispricing rather than to cause it to deepen.

I. Data and Empirical Design

To test our hypotheses we begin by measuring returns to arbitrage strategies. We do this at the aggregate level, by constructing an actively managed portfolio designed to trade based upon common characteristics (other than market beta) that predict the cross-section of stock returns. Testing our hypotheses also requires that we identify proxies for market-wide and performance-based funding constraints, and construct a measure of flows to arbitrage funds.

A. Measuring Returns to Arbitrage Strategies

We begin by simulating an Actively Managed Trading Strategy (abbreviated AMTS), designed to trade on evidence of cross-sectional return predictability documented in academic research.\(^3\) This

\(^3\) We took several steps to produce a simulated trading strategy that is as realistic as possible from an industry perspective. We read numerous research manuscripts produced by leading industry analysts, such as the weekly “What Works” bulletin published by Credit Suisse. We also examined actual research data produced by leading industry analysts such as Credit Suisse’s “Alpha Score Card,” in which individual stocks are ranked on several predictors of cross-sectional returns, such as price momentum and value. Finally, we interviewed a large number of actual fund investors and active managers in New York City, and at the annual meetings of the Chicago Quantitative Alliance in both Chicago and Las Vegas. Our investigation confirms that active managers actually do trade based upon the momentum, profitability, value, and reversal factors that
strategy consists of taking long positions in stocks with high Momentum, Profitability, Value, and Reversal potential, and short positions in stocks with the opposing characteristics. Each of these four factors is, in turn, computed from two or three sub-factors that are designed to capture different facets of the predictability relation.\(^4\)

Portfolios are formed monthly by taking long positions in stocks that are potentially undervalued, and short positions in stocks that appear to be overvalued according to these four metrics. To minimize the variance of the long-short strategy, we match each stock in the long portfolio with a corresponding stock in the short portfolio that belongs to the same industry classification (Johnson, Moorman and Sorescu (2009)). The portfolio is rebalanced monthly. The Appendix provides full details on the construction of AMTS.

By construction, returns to the simulated AMTS are intended to capture the degree of cross-sectional pricing inefficiencies at the beginning of the holding period. For example, a particularly high AMTS return during the month of March is indicative of high cross-sectional inefficiencies at the end of February, provided (of course) that prices at least partially converge towards their equilibrium values.

As discussed earlier, the literature provides a variety of explanations for cross-sectional predictability in stock returns, ranging from time-varying expected returns to psychological biases. Several dynamics (even partially) may contribute to the observed individual returns to characteristics.\(^5\) The AMTS selection algorithm is designed to identify stocks that are most likely to be mispriced: those

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\(^4\) For example, the Profitability factor is computed using the average of Return on Assets and Returns on Invested Capital.

\(^5\) For example, the literature suggests that momentum profits can be the result of investor underreaction, overreaction, and/or time-varying expected returns. If momentum profits are the result of some combination of all three, purchasing winners will help to correct mispricing when the winner stocks are undervalued, but increase mispricing if winner stocks are overvalued. The correction of mispricing will thus only represent a portion of the profits to the momentum strategy where the remainder is either risk compensation or profiting by pushing prices away from fundamental value. In certain states of the world aggregate trading on momentum may reduce mispricing on average, but in some states of the world it may actually increase mispricing on average. Under this scenario, it is not clear that flows of funds to momentum strategies by themselves would tell us anything about the future profitability of momentum strategies (or the aggregate level of mispricing).
with extreme scores across all four individual attributes. Therefore, our empirical tests are based upon returns to the composite AMTS mispricing measure, rather than returns to individual characteristics.

**B. Measuring Funding Constraints**

The ability of fund managers to raise arbitrage capital is affected by performance-based constraints, and by market-wide constraints, both of which affect investors’ willingness to allocate funds to arbitrage strategies.

1. **Performance-Based Constraints**

Performance-based funding constraints are due to an asymmetric information problem between fund managers and investors (Shleifer and Vishny, 1997). The asymmetry arises because investors only observe the level and volatility of past returns, but not the manager’s ability to exploit market inefficiencies and deliver abnormal returns, known as “alpha.” We conjecture that this asymmetric information leads to a rationing in the market for arbitrage capital, in a manner that is conceptually similar to the credit rationing model developed by Stiglitz and Weiss (1981). We argue that investors are less willing to provide capital to managers following periods of low returns (or high volatility during low return periods), because under such conditions investors are unable to ascertain whether this bad performance is due to bad luck or to incompetence. To compensate for this asymmetric information, investors could demand that managers pay out a higher fraction of the alpha generated by the arbitrage strategy; however, doing so could chase away many good managers and skew the remaining pool of managers towards individuals who are either less able or less well intended.⁶ Thus, following periods

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⁶ This argument is analogous to that in Stiglitz and Weiss (1981), where credit is rationed because a rise in interest rates disproportionately skews the remaining borrowers’ pool towards high-risk borrowers with low probability of repayment. Since interest rates alone are not sufficient to clear the market when there is excess demand for credit, there is rationing. Analogously, here, if investors demand a higher share of expected arbitrage profits (or “alpha”) because they perceive the efficacy of an actively-managed strategy to be low, this rations the supply of arbitrage capital because by demanding such higher share of profits, investors will price out good managers and instead attract primarily unskilled managers who do not
when AMTS returns are negative, arbitrage capital becomes rationed and fund managers are less able to raise the funds needed to trade on the perceived market inefficiencies.

Arbitrage capital can also become rationed if the arbitrage strategy is perceived as risky by arbitrageurs. Following a well-established convention in active management, we measure AMTS risk using the denominator of its Sortino ratio (Sortino and van der Meer, 1991). That is, we compute the standard deviation of only negative AMTS returns, replacing all positive AMTS returns with zero. We refer to this measure as the “Sortino volatility” (NSTD). NSTD is intended to capture primarily the downside risk of AMTS, the type of risk that is most carefully watched by active managers.

In the end, the effect of performance-based funding constraints is that periods of poor AMTS performance or high NSTD lead to less arbitrage capital available in the future.

We construct two performance-based constraint variables, at the monthly level:

**AMTS**: The gross monthly return to the Actively Managed Trading Strategy. Periods of low AMTS could coincide with high adverse selection in the market for arbitrage capital, as investors are unable to determine if the poor performance is due to bad luck or to bad management. This type of adverse selection could lead to rationing of arbitrage capital, resulting in lower future flows to arbitrage strategies.

**NSTD**: The Sortino volatility, or standard deviation of the negative portion of the daily return series, \( \min(0, \text{daily return}) \), computed monthly. Periods of high NSTD may indicate high adverse selection in the market for arbitrage capital, as investors are more worried about downside (as opposed to upside) volatility. Such periods are also expected to be followed by lower future flows to arbitrage strategies.

have an alpha-generating technology. A model containing a theoretical framework for this credit rationing effect is available from the authors on demand.
2. Market-Wide Constraints

Market-wide constraints are increases in aggregate borrowing costs, which reduce the aggregate level of capital that can be raised by arbitrageurs. Higher borrowing costs induce redemptions from arbitrage strategies when investors face liquidity shocks elsewhere in their portfolios. Higher borrowing costs also offer more attractive investment opportunities in the fixed income space, which compete with arbitrage-based strategies. Borrowing costs have been shown to impede arbitrage in the context of closed end mutual funds, where a positive relation exists between the absolute discount and the 30-day T-Bill rate (Pontiff, 1996).

An increase in borrowing costs can result from an increase in base interest rates such as 30-day T-Bill or LIBOR, or from an increase in risk-related spreads such as the TED spread (3-month LIBOR minus 3-month T-Bill) or the credit spread (yield on BAA minus yield on AAA). Other aggregate market conditions such as price uncertainty could also make it difficult to implement arbitrage strategies. When price uncertainty is high, investors are less likely to invest in actively managed strategies and are less likely to hold leveraged positions. Increases in transaction costs make marginal arbitrage opportunities infeasible, while feasible arbitrage opportunities become less profitable. All else equal, an increase in market-wide funding constraints will impede flows to arbitrage strategies.

We construct five market-wide funding constraint variables that affect the arbitrageurs’ ability to raise capital. These variables are constructed at the monthly level:

LIBOR: The one-month London InterBank Offered Rate obtained from Bloomberg. Higher LIBOR rates indicate higher borrowing costs, which could force redemptions out of equity funds. Higher LIBOR rates also increase the relative attractiveness of fixed income investment opportunities, resulting in fewer funds available for arbitrage strategies.

TED3: The TED spread computed as the difference between the three-month LIBOR and the three-month T-Bill rate, also obtained from Bloomberg. A high TED spread captures instances of
particular illiquidity in the lending market when interbank loans command a significant premium over the Treasury rate. This could increase the probability of redemption out of equity funds, into more liquid assets.

**CRDSPRD**: The credit spread computed as the difference between BAA corporate bond yields and AAA corporate bond yields obtained from the St. Louis Federal Reserve. Higher CRDSPRD denotes a higher cost of risk, or an increase in aggregate risk aversion. This could cause a “flight to safety” of capital from the equity market toward the fixed income market.

**AGGIVOL**: An aggregate measure of idiosyncratic volatility computed as the equal-weighted monthly average of idiosyncratic volatility for NYSE common stocks. Higher AGGIVOL increases the probability that investors will face margin calls due to losses in other equity investments they might hold, in addition to arbitrage strategies. Margin calls can cause investors to redeem funds from arbitrage strategies in order to cover these losses. Investors could reduce aggregate arbitrage capital either in response to a direct margin call, or in anticipation of the increased risk of forced selling due to margin calls. Higher AGGIVOL also suggests higher arbitrage costs because it is more difficult to find matched pairs of long and short stocks that share a similar risk profile (Pontiff 2006).

**RETDISP**: An aggregate measure of return dispersion computed as the cross-sectional standard deviation of large NYSE common stocks (largest decile). As with AGGIVOL, higher RETDISP also suggests a higher probability that investors will face margin calls in other equity investments, due to losses on individual securities. Again, margin calls and aggregate margin reductions can lead to redemptions from arbitrage strategies.

### C. Measuring Funding Flows

To compute flows to arbitrage strategies we identify a subset of mutual funds whose trading strategies are – at least in part – based upon cross-sectional predictability in stock returns. We do this
by searching for funds whose monthly return performance loads significantly on the AMTS return vector. The loadings are calculated using rolling five-year regressions where excess monthly mutual fund returns are regressed on excess market return, and AMTS. To control for market liquidity risk, we also include an Amihud-based long-short return factor.\(^7\) To be retained in the sample, a fund must have at least 36 monthly observations for each of the 60-month fund-level regressions, and a non-missing monthly flow value.

Funds with a statistically significant and positive loading on AMTS (t-statistic \(\geq +1.96\)) are more likely to trade on the type of cross-sectional return predictability that is embedded in AMTS’ construction algorithm. However the extent to which a mutual fund does follow this algorithm varies significantly from one fund to another. A univariate analysis of all significant loadings on AMTS shows that the cutoff values for the 1\(^{st}\) and 99\(^{th}\) percentiles are 0.025 and 0.761, respectively.\(^8\) These loadings carry an intuitive interpretation as they represent the approximate percentage of fund assets that are invested in a manner similar to the AMTS strategy. To ensure a meaningful economic exposure to AMTS, only funds with AMTS loadings equal to, or greater than, the cross-sectional median coefficient are used in the calculation of MFFLOW, our main proxy for the flow to arbitrage strategies. For the period 1991 to 2009, the median monthly coefficient estimate ranges from 0.10 to 0.31. Thus, our procedure is likely to identify actively managed mutual funds who allocate more than 10% to 30% of their assets to an investment strategy that contains one or more return predictability factors embedded in AMTS’ construction algorithm.

Although mutual funds generally take long-only positions, their trades can still contribute to bringing prices toward efficiency to the extent that funds buy stocks that are perceived to be

\(^7\) The Amihud factor is constructed based on the equal-weighted return differential between the extreme deciles of portfolios sorted each month on the Amihud (2002) illiquidity measure.

\(^8\) The minimum and maximum values of AMTS loadings are 0.01 and 1.72, undoubtedly outliers resulting from the estimation process.
undervalued and sell stocks that are perceived to be overvalued by the AMTS algorithm. Of course, not all mutual funds follow a trading strategy that mimics AMTS; however, among those funds that do, their aggregate flow can act as a channel through which market efficiency is maintained.

We obtain monthly mutual fund returns and total net assets from the CRSP Survivor-Bias-Free US Mutual Fund Database for all existing mutual funds. Because monthly net total assets are not available prior to 1991, all monthly flow variables are calculated during the period from 1991 to 2009.

We begin by computing a measure of fund flows into each of the mutual funds available in the CRSP database (FLOW). Similar to Huang, Wei, and Yan (2007) and to Gil-Bazo and Ruiz-Verdu’ (2009), we compute, for the period 1991 to 2009, the monthly flow to mutual fund \( i \), as follows:

\[
\text{Flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + MRET_{i,t})}{TNA_{i,t-1}},
\]

where \( TNA_{i,t} \) is the total net assets of mutual fund \( i \) at time \( t \), and \( MRET_{i,t} \) is the period return of mutual fund \( i \) at time \( t \), net of fees.

The monthly aggregate fund flow to arbitrage strategies (MFFLOW) is computed using the FLOW measures from funds whose monthly return series loads significantly on AMTS \( (t \geq 1.96) \), and whose regression coefficient is higher than the sample median. Assuming that \( N \) mutual funds meet such criteria, we compute MFFLOW as follows:

\[
\text{MFFLOW}_{i,t} = \frac{\sum_{i=1}^{N} (TNA_{i,t} - TNA_{i,t-1} \times (1 + MRET_{i,t}))}{\sum_{i=1}^{N} TNA_{i,t-1}}.
\]

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\(^9\) As the number of funds becomes arbitrarily large, the aggregate portfolio of actively managed mutual funds will resemble a two-part strategy of holding the market portfolio and holding a long minus short active strategy. The combined strategy will result in actively managed funds holding the market portfolio that is overweight (relative to the market portfolio) undervalued stocks and underweight expensive stocks. As such, mutual funds do not have to “short” overvalued stocks, but rather underweight their aggregate positions relative to the market portfolio weights. That is, funds that hold the overvalued stocks will reduce their positions, while those that don’t hold these stocks are not required to take a short position.

\(^{10}\) Gil-Bazo and Ruiz-Verdu’ (2009) and Huang, Wei, and Yan (2007) calculate flows for individual mutual funds on annual and quarterly horizons, respectively. Our measure, MFFLOW, is a monthly value-weighted average of the individual fund flows.
D. Control Variables

For our hypothesis testing we also control for aggregate illiquidity, flows to non-arbitrage mutual funds, and aggregate market performance.

Using market illiquidity controls for the possibility that investors may decide to abstain from the equity market during periods of high illiquidity (expecting that higher trading costs may be passed on to them via lower realized returns), thus reducing fund flows, and that arbitrage may be difficult in illiquid markets. We use two measures of aggregate illiquidity. The first measure, AILLIQ, is an equally weighted measure of aggregate market illiquidity based on Amihud’s (2002) illiquidity measure. Following Watanabe and Watanabe (2008), AILLIQ is computed as equally weighted average of the monthly firm level illiquidity measure. To be included in AILLIQ, a firm must have at least 15 daily observations containing valid return and dollar volume data. The second measure, TURN, is an aggregate measure of share turnover calculated as an equally weighted monthly average of trading volume, divided by shares outstanding. Lower values of TURN correspond to higher values of aggregate illiquidity. These two control variables are constructed monthly using all common stocks in the Center for Research in Security Prices (CRSP) database that are listed on NYSE. We exclude all stocks with share prices lower than $5 and higher than $1,000 at the end of the previous month.

To better isolate the relation between flows to funds that mimic AMTS and returns to AMTS, we also control for MFFLOWX, the aggregate fund flows across mutual funds whose return vectors do not load on the AMTS vector with a statistically significant positive coefficient (t-statistic < +1.96). Assuming K funds, we compute MFFLOWX as follows:

\[
MFFLOWX_{i,t} = \frac{\sum_{i=1}^{K} (TNA_{i,t} - TNA_{i,t-1}) \times (1 + MRET_{i,t})}{\sum_{i=1}^{K} TNA_{i,t-1}}.
\]
Lastly, we control for aggregate stock market performance (Rm-Rf), measured as the difference in monthly returns between the value-weighted market index and the one-month Treasury bill rate (obtained from Ken French’s website).

II. Descriptive Statistics

We begin by examining the performance of AMTS, our actively managed trading strategy, in order to assess the degree of cross-sectional market efficiency in our sample. The results, presented in Table 1, are based on monthly rebalancing of AMTS. However, results based on longer rebalancing periods remain qualitatively similar. Table 1 shows the gross and net returns to AMTS for the period 1967 to 2009. The net returns account for transaction costs, which include commission as well as the price impact of trade. As can be seen, AMTS returns are significantly positive and remarkably persistent throughout the sample period. We divide the sample into four sub-periods, each of which corresponds roughly to a different decade. In each sub-period, the AMTS portfolio dominates the S&P500 with a lower standard deviation and higher (or equal) average return. This performance is quite remarkable given that AMTS’ appropriate benchmark is not the market return but rather the risk-free rate.

A long-short hedge strategy that invests 130% in the long AMTS positions and 70% in the short AMTS positions also dominates the S&P 500, in that it has slightly lower volatility and higher average returns over the full period as well as each sub-period. While AMTS is clearly not riskless, long-term

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11 Trading cost estimates include both commissions as well as price impact of trade. Historical commissions are obtained from Jones (2002). Estimates of the price impact of trade are from Hasbrouck (2009) using the Gibbs estimate of trading costs. These estimates assume $1 billion of assets under management in December 2009. For previous years, we deflate the $1 billion amount using the value weighted market index (including dividends) obtained from CRSP.

12 Because AMTS is, by design, a market-neutral, zero-beta strategy, its appropriate benchmark is the risk-free rate. Nonetheless, we compare it here with the S&P500 to illustrate the extraordinary performance of this strategy over several decades.

13 This strategy is referred to as “130/70” in the industry. It is designed to take advantage of potential cross-sectional inefficiencies ($70 long for every $70 short), while still allowing participation on the long side of the market ($60 net long) in order to earn the long-term equity premium.
returns to this strategy substantially outperform a passive investment in the S&P 500 over the sample period.

Table 2 shows the relative contribution of each of the four mispricing factors (momentum, short-term reversal, profitability, and relative value) to the performance of the AMTS over the period 1967 to 2009. To measure the relative contribution of each factor we create long-short strategies based on each measure of mispricing, and all possible combinations of the four measures, and compute Information and Sharpe ratios.\(^\text{14}\) Over our sample period a strategy based on short-term reversal had the highest relative performance of the individual strategies. The combination of reversal and profitability was higher than reversal alone and is the highest of the two-strategy combinations. Overall, Table 2 demonstrates that each of the four measures contributes to the overall performance of AMTS.\(^\text{15}\)

The strong AMTS performance over more than four decades seems to suggest a chronic level of pricing inefficiencies in the cross-section of US stock returns. AMTS’ strong performance is particularly puzzling during the most recent decade, given the large number of funds that actively trade on this strategy, as well as the vast amount of information (especially from academic research) available to fund managers about cross-sectional return predictability. Our explanation is that AMTS’ persistent outperformance is due to time-varying constraints on arbitrage capital.

Table 3 provides summary statistics of our key variables. Panel A covers the full sample period (1967 to 2009), while Panel B covers the period corresponding to the availability of mutual fund data (1991 to 2009). The distribution of NSTD is similar across the two sample periods. Also of interest, aggregate illiquidity decreases (and turnover increases) in the second period, relative to the full sample.

\(^{14}\)To obtain the information ratio we regress monthly returns to the strategy returns on the excess market returns and a constant. The information ratio is computed by dividing the intercept by the standard deviation of the residuals. To obtain the Sharpe ratio we regress the monthly returns of the strategy returns on a constant. The Sharpe Ratio is computed by dividing the intercept by the standard deviation of the residuals.

\(^{15}\)The weakest contribution is from momentum. This result is largely due to the momentum crash in April 2009 (see Daniel and Moskowitz (2011) for additional details). Excluding April 2009, the momentum strategy performs significantly better.
Table 4 provides pair-wise correlations between the key variables. The correlation between AMTS and NSTD is strongly negative for both sub-periods, suggesting that periods of high Sortino volatility also correspond to lower contemporaneous AMTS returns. AMTS is negatively correlated with TURN and positively correlation with AILLIQ, indicating that periods of higher aggregate liquidity are associated with higher market efficiency which manifests in the form lower future returns to AMTS.

**III. Results**

We now present our main empirical results for the period 1991 to 2009. The period starts in 1991 because monthly net total assets for mutual funds are not available prior to that date. This start date is also closely aligned with the initial publication of key papers related to the momentum (Jegadeesh and Titman (1993)) and reversal (Jegadeesh (1990), Lehmann (1990)) literature. This makes it reasonable to assume that at least some of the market participants during this period were aware of these two cross-sectional return predictability relations.

**A. The Effect of Funding Constraints on Mutual Fund Flows**

To test hypothesis H1 in the introduction, we examine the relation between constraints on arbitrage capital and flows to arbitrage strategies. When capital constraints are high, we expect lower arbitrage flows to mutual funds whose trading strategies correlate with AMTS’ algorithm. We expect that funding constraints will impede arbitrage flows *with a time lag*, especially for performance-related constraints where investors need to observe fund performance before making their asset allocation decision. However, we have no priors about the extent of that lag. In preliminary tests we have found that the relation is strongest when the time lag is set to one or two months, and in many cases the relation also holds on a contemporaneous (zero-lag) basis. We report our main results with funding constraints measured over the most recent two months (the \([t-2, t-1]\) window).
Table 5 presents the results. Panel A of Table 5 examines the relation between funding constraints measured over the \([t-2, t-1]\) period, and arbitrage flows measured at time \(t\) (MFLOW(t)). The top two lines in Table 5 examine the effect of performance-based funding constraints. The first two model specifications in Panel A provide a direct test for H1. The results are consistent with our hypothesis. The coefficient on AMTS is positive and significant with an estimate of 0.081 (\(t = 2.10\)) for the period 1991-2009. The coefficient on NSTD is negative and significant with an estimate of -2.32 (\(t = -2.52\)). Together, these results support the notion that poor past performance leads to lower arbitrage flows in the future.

The next five lines in Panel A provide support for the second part of H1. Proxies for market-wide constraints are negatively related to future flows, and the relations are significant except in the case of the credit spread (CRDSPRD) proxy, which nonetheless carries the correct sign. The results using the LIBOR proxy are only marginally significant. However, the relation is strongly significant when using TED3, with a coefficient estimate of -0.008 (t-statistic= -2.71). Similarly, the relation remains strongly significant in the case of idiosyncratic volatility (coefficient estimate -1.156, t-statistic= -3.67), and cross-sectional return dispersion (-0.232, t-statistic= -4.43).

The last section of Panel A shows the loadings on three control variables. The coefficient on MFFLOWX, the flow to non-arbitrage funds, is not statistically significant. The coefficient on the market term (Rm-Rf) is positive and strongly significant; investors appear more likely to allocate money to equity funds following strong market performance. The coefficient on AILLIQ is always positive, but is (marginally) significant only in four out of the seven cases, suggesting that the link between flows to arbitrage funds and aggregate illiquidity is positive, but not strong.

In Panel B of Table 5 we repeat the analysis in Panel A, except that we now use separate monthly values for independent variables at time (t-1) and (t-2), instead of using their aggregate two-month averages \([t-2, t-1]\). The results are consistent with those reported in Panel A. All coefficients
carry the correct sign, and the coefficients measured at (t-1) are all statistically significant at the 10% level or better.

In untabulated results we repeat the analysis in Panel A, measuring now proxies for funding constraints *contemporaneously* with the flows to actively managed strategies. Coefficient estimates on measures of past performance and proxies for market-wide constraints are largely unchanged from the estimates obtained in Panel A.

Overall, the results presented in Table 5 demonstrate that flows to actively managed funds are positively related to past AMTS returns, negatively related to the Sortino volatility (NSTD) of past AMTS returns, and negatively related to proxies for market-wide constraints on arbitrage capital. Moreover, these results suggest that funding constraints impede fund flows not only in real time, but also up to one or two months into the future. Our results provide strong support for H1: raising arbitrage capital is more difficult in the presence of performance-based constraints and market-wide constraints to arbitrage capital.

**B. The Effect of Mutual Fund Flows on Future AMTS Returns**

We now examine the extent to which flows to arbitrage funds affect market efficiency. High flows allow arbitrageurs to trade mispriced stocks and reestablish market efficiency, resulting in less cross-sectional predictability and lower AMTS returns in the future. By contrast, when flows are low, arbitrage constraints are relatively binding, and the market is less efficient from a cross-sectional perspective. In this case, future AMTS returns are higher as prices eventually converge toward fundamental value.
1. Abnormal Fund Flows

Our base variable, MFFLOW, measures flows into funds that load significantly on AMTS. However, from an inter-temporal perspective, aggregate fund flows increase significantly over the sample period, and changes in MFFLOW may also capture effects of aggregate flow increases (in addition to capturing the effects of capital constraints). Indeed, the aggregate total net assets of mutual funds in our dataset increased from approximately $865 billion to $9.7 trillion over the sample period from 1991 to 2009, and MFFLOW does not account for changes in these aggregate flows.

To control for aggregate flow effects, we use *abnormal fund flows* (rather than raw fund flows) to explain the future profitability of AMTS. Our abnormal flow variable, ABNMFFLOW6, captures flows to mutual funds that load significantly on AMTS factor, net of trends in aggregate flows (to both AMTS Funds and non-AMTS funds). We also control for flows that may not be directly related to arbitrage constraints. ABNMFFLOW6 is measured as the residuals obtained by regressing MFFLOW on past flows and controls, according to the following specification:

\[
MFFLOW_t = a_t + \sum_{i=1}^{6} b_{1,i} * MFFLOW_{t-i} + \sum_{i=1}^{6} b_{2,i} * MFFLOWX_{t-i} + b_3 * (RM - R_f)_{t-1} + b_4 * AILLIQ_{t-1} + e_t \tag{4}
\]

The ABNMFFLOW6 measure captures innovations in flows to arbitrage funds that are not related to changes in the aggregate level of flows to mutual funds. Table 6 presents the regression results. The six columns of Table 6 explore different specifications ranging between one and six lags for the MFFLOW and MFFLOWX variable. The six-lag specification was selected due to the statistically significant coefficient on MFFLOWX (t-6). However, the results are robust to other specifications as well.

2. Relation between Abnormal Flows and Future AMTS Returns

Recall that returns to AMTS result from the convergence of cross-sectional stock prices toward fundamental values during the month when returns are measured. These returns are determined by
the level of mispricing at the beginning of each month and price convergence during the month. The level of mispricing at the beginning of each month is a function of the flow of arbitrage capital in prior periods. When arbitrage capital is constrained, there should be relatively lower flows to arbitrage funds, which should result in a relatively less efficient market and higher future returns to AMTS as price convergence takes place with a time lag. In contrast, when arbitrage capital flows freely, we expect prices to more closely reflect fundamental values, resulting in lower AMTS returns in the future. Thus, as per our hypothesis H2, we expect a negative relationship between flows to arbitrage funds and future AMTS returns. We now provide a formal test for H2; specifically, we look for a negative relation between ABNMFLOW6 (our measure of abnormal flows to arbitrage funds) and future AMTS returns (our proxy for cross-sectional return predictability).

Table 7 presents the results. Monthly returns to AMTS are regressed on lagged abnormal flows (ABNMFFLOW6). We also include the previous measures of capital constraints and control variables used in Table 5. In Panel A of Table 7, all independent variables are measured with a lag over a two-month period [t-2, t-1]. As conjectured, the relation between abnormal mutual fund flows (ABNMFFLOW6) and future AMTS returns is negative and significant for all empirical specifications, suggesting that cross-sectional market efficiency is weaker when flows to arbitrage funds are more restricted. Interestingly, coefficients of MFFLOWX are positive and significant, suggesting that cross-sectional market efficiency is also weaker following periods when flows to non-arbitrage funds are unusually high. The funding constraint variables and the remaining control variables (with the exception of turnover (TURN)) are generally insignificant in the presence of abnormal fund flows (ABNMFFLOW6). This suggests that the effects of constraints on arbitrage capital are subsumed by the fund flow variables. These constraints do not appear to impede market efficiency beyond the effect that operates through the fund flow measure.
In untabulated results, we repeat the analysis in Panel A, except that we measure the capital constraint variables contemporaneously to the dependent variable (AMTS), while the abnormal flow continues to be measured with a lag. The results are almost identical to those presented in Panel A.

In Panel B of Table 7 we use separate monthly values for independent variables at time (t-1) and (t-2), instead of their aggregate two-month averages [t-2, t-1]. The coefficient estimates on lagged abnormal flows are negative at both the first and second lags, but are generally weaker than the results in Panel A, perhaps due to low test power. The coefficient estimates are stronger at the second lag, suggesting that it takes approximately two months for mispricing to be corrected following periods of acute funding constraints.

In untabulated results, we explore a variant of the Panel B specification, using exclusively independent variables measured at (t-2). We find that abnormal flows are negatively and significantly related to future AMTS returns, consistent with the findings presented in Panel A.

In Panel C of Table 7, we explore an alternative measure of fund flows. Instead of using abnormal flows obtained from the time series model in equation (4), we use the actual flows to AMTS funds, scaled by the aggregate market capitalization of stocks in the AMTS portfolio. This scaled flows measure captures the importance of flows relative to the size of the AMTS portfolio. In contrast, the previous measure, abnormal flows, captures the importance of flows relative to their past history. These two measures capture different facets of the relation between flows and market efficiency. The abnormal flows measure captures the unexpected dollar amount of arbitrage capital available in any month. The scaled flow measure captures the ability of flows to move stock prices toward their fundamental value. Consistent with the results presented in Panels A and B, we continue to find a negative and significant relationship between future returns and fund flows scaled by the market capitalization of AMTS stocks, but this relation is confined to the one-month lag (t-1).
Overall, the results presented in Table 7 provide strong support for H2: future AMTS returns are negatively and significantly related to abnormal flows to mutual funds that seek to exploit cross-sectional return predictability. This is consistent with the main theme in our paper: low abnormal fund flows correspond to high constraints for arbitrage strategies, resulting in lower market efficiency and higher future returns to arbitrage strategies such as AMTS.

IV. Additional Tests and Alternative Hypothesis

We now conduct a series of tests to assess the our results under different assumptions and empirical specifications, and also consider an alternative explanation for our results.

A. Risk-Adjusted AMTS Returns

We begin by repeating the analysis from Panel A of Table 7 with a risk-adjusted dependent variable. The dependent variable is now constructed as the raw return to AMTS minus the expected AMTS return obtained from a market model estimated over 60-month rolling windows. Although AMTS is a long-short strategy designed to have a beta of zero, we include the market factor (RM-RF) in our model to account for any possible deviations from the zero-beta theoretical level. The results (not tabulated) are very similar to those presented in Table 7, indicating that the relation between abnormal flows and AMTS cannot be explained by the market risk factor.

B. Contemporaneous Relation between Flows and AMTS Returns

While the focus of this paper is the relationship between constraints on arbitrage capital and return predictability (future AMTS returns), our “limit to arbitrage” hypothesis also carries an implication regarding the contemporaneous relation between arbitrage flows and AMTS returns. Recall
that abnormally high arbitrage flows are expected to accelerate price convergence, while abnormally low flows are expected to induce a delay in convergence. If abnormally high flows accelerate convergence, we could observe a positive contemporaneous relation between abnormal flows and AMTS returns, assuming that a sufficient movement toward convergence occurs during the month when abnormal flows are measured.

This relation should be stronger if we condition on months when initial cross-sectional mispricing is more pronounced. For example, if cross-sectional mispricing is large at the beginning of January, high abnormal flows during January will likely correct mispricing and result in positive AMTS returns, while low abnormal flows during January will likely leave the mispricing unchanged, producing AMTS returns close to zero. This phenomenon implies a positive contemporaneous relation between abnormal flows and mispricing, conditional upon mispricing being high at the beginning of the month.

By contrast, if we condition on months with lower initial cross-sectional mispricing, we would expect to see a much weaker contemporaneous relation between flows and AMTS returns, since arbitrage flows do not contribute as much toward price convergence.

We begin by examining the unconditional relation between abnormal flows and AMTS returns, using a model similar to that presented in Table 7. The results (untabulated) show that the relation is indeed positive but does not attain statistical significance (t= 0.96). A possible explanation for the lack of significance is the existence of a time delay between flows to AMTS funds and trading in AMTS stocks. For example, if the flow occurs at the end of the month, funds might not be invested until the following month, thus biasing our results toward zero. Further, flows from the prior month, invested in AMTS stocks during the current month, would inject additional noise into our results. An alternative explanation is that convergence may not occur until a critical mass of arbitrage capital is achieved. If arbitrage funds do not have perfect foresight, there may be a delay between the individual funds investment and price convergence.
We next examine the conditional relation between abnormal flows and AMTS returns, as a function of the degree of mispricing prevailing at the beginning of each month. We use abnormal flows during the previous month as a proxy for the degree of mispricing at the beginning of each month. Months preceded by high abnormal flows are likely to present with lower cross-sectional mispricing on the first day, because any mispricing would have already been corrected in the previous month. By contrast, higher cross-sectional mispricing should be present at the beginning of months preceded by low abnormal flows. During such months, the relation between flows and contemporaneous AMTS returns should be stronger.

To test this conditional hypothesis we first divide all calendar months into two groups, according to the sign of abnormal flows in the previous month. We then further divide each group according to the sign of abnormal flows during the current month. We measure the average return to AMTS in each of the four groups.

The results (untabulated) are consistent with our hypothesis. We first examine months preceded by low abnormal flows, the most susceptible of having initial cross-sectional mispricing. Among those, months with high contemporaneous abnormal flows exhibit an average AMTS return equal to 1.34% per month. The monthly AMTS return drops to 0.72% among months with low contemporaneous abnormal flows. The difference between the two groups (0.62% per month) is quite large in economic terms, but does not attain statistical significance, perhaps because the power of the test is quite weak given that the standard error is computed from a limited number of monthly observations. Moving now to months preceded by high abnormal flows, we find almost no effect of contemporaneous flows on AMTS return, consistent with the hypothesis that this is a group of months with lower initial cross-sectional mispricing.

Another implication of our hypothesis is a positive contemporaneous relation between AMTS returns and changes in institutional holdings of AMTS stocks. If institutional investors purchase relatively
undervalued securities and sell relatively overvalued securities, their trades should be positively correlated with contemporaneous AMTS returns as the trading actively causes prices to converge towards fundamental value. To test this, we calculate quarterly changes in institutional holdings of AMTS stocks, using the Thomson-Reuters Institutional Holdings (13F) Database. We then run pairwise correlations between AMTS returns (also measured quarterly), and contemporaneous changes in institutional holdings of AMTS stocks. Consistent with our prediction, the results (untabulated) show that changes in institutional holdings are positively correlated with contemporaneous AMTS returns (the magnitude of the correlation is 0.088), but the relation is not statistically significant. The lack of significance could be due to lower statistical power resulting from measuring returns and holdings over three-month periods, a limitation imposed by the 13F data.

C. Addressing the “Dumb Money” Hypothesis

An alternative explanation is possible for the negative relation between fund flows and future AMTS performance. Frazzini and Lamont (2008) document a “dumb money” effect, whereby money from unsophisticated investors flows into investment funds with better recent performance, causing stocks in these funds to become mispriced. According to the dumb money hypothesis, when flows to arbitrage strategies such as AMTS are unusually high, fund managers will invest the new proceeds according to the funds’ established active management algorithm, causing the underlying “long” stocks to become overvalued, and the underlying “short” stocks to become undervalued. Over the longer term, any mispricing induced by abnormal flows will correct, and stocks prices will converge to fundamental values.

The “dumb money” hypothesis differs fundamentally from the “limits-to-arbitrage” hypothesis presented in our paper. The “dumb money” hypothesis predicts that flows to arbitrage funds drive
stock prices away from their fundamental values, and that this mispricing corrects over time generating the observed return reversal in the stocks that had high recent flows.

By contrast, the “limits-to-arbitrage” hypothesis predicts that as mispricing arises from exogenous sources, such as unsophisticated investors, flows to arbitrage strategies drive stock prices toward their efficient levels. The negative relation between flows and future AMTS returns is due to the reduction in future return predictability (that results from lower aggregate mispricing), rather than return reversal in the underlying stocks. If flows to AMTS funds are “dumb money,” then they should drive prices away from fundamental value (during the period of the flow), and we should observe a positive relationship between flows and return predictability rather than the negative relationship demonstrated in Table 7. Alternatively, if we assume that “dumb money” flows today continue to affect prices in future periods, prices may continuing to diverge from fundamental value resulting in a negative relationship similar to that observed in Table 7. However, prices should eventually correct over longer holding periods.

In terms of empirical implications, the main difference between the “dumb money” explanations and our “limits to arbitrage” hypothesis is that the former explanation predicts return reversal in the relation between flows and future returns of the underlying AMTS stocks, while the latter does not.

We conduct three separate tests to evaluate the “dumb money” hypothesis. First, we extend the holding period in the AMTS portfolio to test for the return reversal suggested by the “dumb money” hypothesis. The main AMTS portfolio is rebalanced monthly, each month selecting stocks that score highest according to the value, profitability, momentum and reversal factors. In this robustness test, we increase the rebalancing period progressively from 2 to 12 months. The portfolio trades still take place monthly, but each vintage of stocks is now held for more than one month. This will result in two or more overlapping generations of stocks held in the portfolio at any given time. For example, when the
holding period is three months, on March 29 the portfolio will include positions open on January 1st (held until April 1st), February 1st (held May 1st) and March 1st (held until June 1st). If the “dumb money” explanation is correct, returns to AMTS should reverse and vanish for longer holding periods. By contrast, under our explanation, AMTS returns should remain significantly positive for longer holding periods, capturing the slow stock price convergence toward fundamental value.

In Table 8 we group all time periods according to the sign of the abnormal flow variable (ABNMFFLOW6). If the “dumb money” hypothesis is correct, we would expect to see reversal in the performance of AMTS for the sub-sample corresponding to positive ABNFFLOW6. Contrary to the dumb money effect, there is no evidence of reversal at any horizon. Table 8 shows that returns are increasing in the holding period suggesting that prices of AMTS stocks do not reverse over any time period of up to 12 months in the positive (or negative) ABNMFFLOW6 subsamples.

In our second test (untabulated), we repeat the analysis in Table 7 by skipping one month between the time when the flows are measured and the time when the AMTS performance is measured. If abnormal funds flowing at month t-2 push stock prices away from equilibrium during that same month, returns to AMTS would be positive during month t-2 and negative the subsequent month (t-1) as prices revert to equilibrium. To control for this possible short-term reversal, we exclude month t-1 from our analysis and measure instead AMTS returns at time t. The results (not shown) are almost identical to those reported in Table 7.

To address whether our results arise from measuring flows over too short of a window, in our third test (untabulated), we repeat the analysis in Table 7 but vary the period over which fund flows are measured, from one month to six months. The results are similar to our findings in Table 7 and suggest that the measurement period of abnormal flows does not alter our results.
Overall, the results presented in this section suggest that, while the “dumb money” effect could exist elsewhere in the financial markets, the “limits to arbitrage” hypothesis provides a more plausible explanation for the cross-sectional predictability in stock returns.

**D. Vector Autoregression Model (VAR)**

Although our results in Table 7 suggest that abnormal fund flows are related to future AMTS performance, the causality of this relation cannot be readily determined from Table 7, especially since Table 5 documents, in a different context, a relation between past AMTS performance and future fund flows. To determine the causality of the relation presented in Table 7 we perform a Vector Autoregression (VAR) analysis where we consider the joint dynamics of AMTS and abnormal fund flows. We use AMTS and ABNMMFLOW6 as endogenous variables, and include control variables specified in Table 7 (TURN, AILLIQ, RM-RF, and MFFLOWX) as exogenous variables in the VAR system.

The results are presented in Table 9. To alleviate concerns about return reversal suggested by the “dumb money effect” discussed earlier, we skip one month by forcing the coefficients on lag 1 to be zero. The top half of Table 9 shows a negative and significant relation between abnormal funds flows (ABNMMFLOW6) and future AMTS performance. Specifically, when flows are unusually low in a given month, the performance of AMTS is unusually high two months later, as measured by the coefficient on the second lag of ABNMFFLOW6 (-0.48, t=-2.06). By contrast, there seems to be no relation between AMTS performance and future abnormal funds flow in the bottom half of Table 9 (t=-0.47). These findings suggest that constraints to arbitrage capital (as captured by abnormal fund flows) result in higher cross-sectional predictability in future stock returns, which corroborates our previous conclusion.

We also study the impulse response of this VAR analysis and present the results in Figure 1. The graphs provide additional corroborating evidence. The middle line in each graph displays the point estimates, while the upper and lower lines display the boundaries of a 90% confidence interval. Figure
1-A shows the response of AMTS to abnormal fund flows. That is, it examines the extent to which abnormal fund flows are useful in forecasting AMTS performance for various lags. The response is negative and significant for lag 2, where the confidence interval does not include zero. The effect remains negative for the third lag, although not statistically significant. For the following lags, the effect is indistinguishable from zero. Figure 1-D shows the abnormal fund flow impulse response to AMTS performance. The relation is not statistically significant: the point estimate is close to zero and the confidence interval appears centered on the zero axis for all lags. Thus, abnormal fund flows appear to be useful in forecasting AMTS performance, but the opposite is not true. Overall, the evidence presented in Figure 1 is consistent with the results of Tables 7 and 9 -- constraints to arbitrage capital lead to future cross-sectional predictability in stock returns.

V. Using Hedge Fund Flows Instead of Mutual Fund Flows

Given restrictions on short sales, the ability of mutual funds to arbitrage overvalued stocks is limited to selling stocks they already own. In contrast, hedge funds are able to take both long and short positions, and are perhaps better situated to arbitrage away overvaluation because they can short sell overvalued stocks that they do not own. Arguably, flows to hedge funds provide a better measure of arbitrage capital when compared to flows to mutual funds. However, using hedge fund data to measure flows imposes several important limitations due to well documented biases (e.g. selection bias, survivorship bias), and due to the fact that most databases cover a limited number of years and a limited number of hedge funds that might not be representative of the population. It is because of these limitations that we use mutual fund flows for our principal set of tests (Tables 5 to 7).

For robustness, we now repeat our core tests using hedge fund flows (rather than mutual fund flows) as a proxy for arbitrage capital. We obtain flows to market-neutral hedge funds from the HedgeFund.net database. The data begins in 1997. We chose market-neutral hedge funds because
these funds -- like AMTS -- are specifically designed to take advantage of cross-sectional mispricing with minimal exposure to the market factor.

A. Time Series Tests

We begin with a set of time-series tests that mirror those performed in Tables 5 and 7 with mutual fund flows. The results are presented in Table 10 and 11.

Table 10 repeats the analysis presented in Panel A of Table 5, substituting mutual fund flows with hedge fund flows. We continue to find a significantly positive relation between fund flows and past returns to AMTS. The relation between hedge fund flows and Sortino volatility is negative, but does not attain statistical significance ($t=-1.62$), perhaps because of the lower power of the statistical tests resulting from the shorter sample period. While the proxies for arbitrage constraints are all negatively related to hedge fund flows, the only two measures that are statistically significant are the cross-sectional dispersion of stock returns (RETDISP, $t=-2.42$), and the aggregate idiosyncratic volatility measure, which is marginally significant (AGGIVOL, $t=-1.64$). Once again, the lack of significance on the other measures could reflect the lower statistical power. Overall, the results presented in Table 10 provide strong support for the notion that performance-based funding constraints affect arbitrage capital, and somewhat weaker support for the second part of H1, that market-wide constraints affect arbitrage capital, when hedge fund flows are used as proxy for arbitrage capital.

Table 11 repeats the analysis in Panel A of Table 7, again, substituting abnormal mutual fund flows with abnormal hedge fund flows. As before, we find that abnormal hedge fund flows are negatively and significantly related to future returns to AMTS with coefficient estimates ranging from -0.034 to -0.037 ($t$-statistics ranging from -2.28 to -2.58). While the proxies for arbitrage constraints were insignificant in the case of abnormal mutual fund flows (Table 7, Panel A), we now find a significantly relation between future AMTS returns and several measures of funding constraints (both
performance-based and market-wide). Specifically, the coefficient on Sortino volatility of AMTS is 4.878 (t=2.12), the coefficient on LIBOR is 3.422 (t=1.82), the coefficient on TED3 is 0.028 (t=2.38), and the coefficient on AGGIVOL is 3.028 (t=1.66). All other coefficients carry the correct sign, with the exception of CRDSPRD. This is an interesting variation on the results obtained with mutual fund flows in Table 7. In the case of mutual funds, the effect of capital constraints on cross-sectional efficiency appears to operate exclusively through fund flows. In the case of hedge funds, this effect operates not only through fund flows (Table 10) but also directly (Table 11). A possible reason for this difference is that unlike mutual fund managers, hedge fund managers frequently make use of margin capital to enter into trading positions, and when borrowing costs rise, their ability to raise margin capital is curtailed.

Overall, the empirical results in Tables 10 and 11 corroborate our previous evidence of time varying market efficiency. We again find the level of cross-sectional market inefficiency, as proxied by the returns to AMTS, is higher when constraints on arbitrage capital are less binding.

B. Vector Auto Regression Analysis

We now turn to a vector autoregressive model, and repeat the analysis presented in Table 9, using hedge fund flows instead of mutual fund flows. The results are presented in Table 12. Consistent with the results obtained with mutual fund flows in Table 9, the top half of Table 12 shows a negative and significant relation between abnormal hedge funds flows (ABNHFFLOW6) and future AMTS performance. Unusually low hedge fund flows in any given month, lead to an unusually high AMTS performance two months later, as measured by the coefficient on the second lag of ABNHFFLOW6 (-0.029, t=-2.24). We continue to find no relation between AMTS performance and future abnormal hedge fund flows, in the bottom half of Table 12 (t=1.39). Overall, the VAR analysis applied to hedge fund flows corroborate our earlier conclusion that constraints to arbitrage capital are associated with greater cross-sectional predictability in stock returns in the future.
VI. Conclusion

We propose that cross-sectional market efficiency, proxied inversely by cross-sectional predictability in future stock returns, varies over time with funding constraints faced by active portfolio managers -- those with the skills and knowledge to exploit such predictability. We argue that investors’ willingness to invest with these managers, and consequently the amount of available arbitrage capital, depends on two factors: (i) market wide capital constraints and (ii) investors’ beliefs about the efficacy of the arbitrage trading strategy, which, in turn, depends on that strategy’s past performance. We provide evidence that arbitrage capital is indeed curtailed in the presence of these funding constraints: flows to arbitrage funds are positively related to the past performance of AMTS (a simulated arbitrage strategy), and negatively related to market-wide constraints on arbitrage capital.

We also document that future returns to AMTS are negatively related to abnormal fund flows to arbitrage strategies. The lack of arbitrage fund flows delays price convergence toward fundamental value, leading to higher cross-sectional predictability in stock returns, and higher returns to AMTS in the future. Thus, constraints on arbitrage capital impede the degree of cross-sectional efficiency.

Our work provides a fertile ground for future research. For example, we have explored one possible active management strategy involving value, momentum, short-run reversals, and accounting profitability. There are other important return predictors, such as accounting accruals (Sloan, 1996), or asset growth (Cooper, Gulen, and Schill, 2008) and the returns to active strategies based upon these other predictors could also vary across time in a manner similar to AMTS. Furthermore, time variation in predictability of equity returns in other countries also is an open question. Funds in countries with more opaque markets could have more difficulty attracting arbitrage capital and such countries could exhibit stronger return predictability. Other important pricing discrepancies such as the yield differential between on- and off-the-run bonds may also time vary with constraints on bond fund managers.
Our work also raises the question of how easy it is to actually earn abnormal returns by trading on cross-sectional predictability. While some talented managers who trade with their own funds might be able to earn these returns, many others who depend on external funds might not. This could explain why most actively managed funds do not outperform their benchmark despite substantial evidence in the finance literature of cross-sectional return predictability. Analyses of these and other issues are left for future research.
References


Appendix

Construction of AMTS

Monthly and daily stock data including price, return, trading volume, and shares outstanding are obtained from the Center for Research in Security Prices ("CRSP") for all securities listed on the NYSE, AMEX, and NASDAQ stock exchanges. Annual and quarterly accounting data are obtained from Standard & Poor’s Investment Services’ Compustat North America ("COMPUSTAT") database. To ensure realistic simulation of trading strategies, all accounting variables are based on quarterly data after 1971 (quarterly data not available prior to that time). Prior to 1972, accounting measures are based on annual data to generate a time series starting January 1964. In both cases, we assume that accounting results are made public two months after the end of the reporting period (we also tried skipping four months for annual data and the results remain substantially the same). For example, consider a firm with a reporting period that ends in March. We assume the accounting information is public by the end of May and used for portfolios held for the month of June. The overall results are substantially similar when the period prior to 1972 is excluded from the sample. To ensure that the trading strategy can be implemented for portfolios with economically significant magnitudes, we exclude from our database all stocks whose market capitalization on December 31, 2009 was less than $1 billion dollars. For prior years, we deflate this cutoff with the CRSP value-weighted market return index. The base dataset also excludes stocks with share prices lower than $5 or greater than $1,000.

A.1. Four Predictors of Cross-Sectional Returns

AMTS is a long-short hedge strategy designed to earn abnormal returns from potential cross-sectional security mispricing, based upon four primary predictors of cross-sectional stock returns: price momentum, short-term reversal, profitability, and relative value. These four measures are derived from
eleven underlying measures that are shown to be correlated to the cross-section of stock returns in the academic literature and are commonly used by industry practitioners (such as the Credit Suisse Alpha Score Card). Details of the four primary measures follow:

**Price Momentum**

Each month stocks are ranked into percentiles based upon three measures of momentum: six-month momentum, six-month industry adjusted momentum, and fifty-two week high.\(^{16}\)

Six-month momentum is calculated as the compounded return for the six months immediately preceding the portfolio formation period. Six-month industry adjusted momentum is calculated as the compounded return for the six months immediately preceding the portfolio formation period minus the equal-weighted average return over the same period for all stocks in the same two-digit COMPUSTAT SIC code. The fifty-two week high is calculated for each stock as the month end price prior to the portfolio formation period scaled by the highest closing price for the twelve months immediately preceding the portfolio formation period. We adjust prices for stock splits and other adjustments to prices over the past 52 weeks.

A momentum “score” for each stock is then calculated as the equally weighted average of the percentiles for these three underlying measures.\(^{17}\) One month is skipped between the measurement period and holding period for all momentum measures to minimize microstructure effects. For example, suppose that Stock X’s past six month returns, when ranked against the universe of stocks in the database, produces a percentile rank of 80. When the same stock’s industry-adjusted past six month returns are ranked against the population of stocks, the percentile rank is 70. And, when the stocks are ranked based upon the 52-week-high metric, Stock X’s percentile rank is 60. In this case, we

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\(^{16}\) See George and Hwang (2005) for evidence on profitability of the 52-week high indicator.

\(^{17}\) The use of equally weighted average for factor scores is common in industry, and to our knowledge, the exchange-traded note CSLS is designed based upon an equally weighted factor algorithm.
would to assign to *Stock X* a momentum score of 70 \([(80+70+60) \div 3]\). The higher the momentum score, the higher the future expected appreciation in the value of a stock according to the actively managed view.

**Short-term Reversal**

Based on the work of Jegadeesh (1990), each month stocks are ranked into percentiles based upon three measures of short-term reversal: one-month price reversal, one-month industry adjusted price reversal, and five-day industry adjusted price reversal.

The one-month reversal is measured as the rate of return during the one-month period immediately preceding the holding period. One-month industry adjusted reversal is computed as the one-month return measured immediately prior to the holding period, minus the equally weighted average return over the same period for all stocks in the same two-digit COMPUSTAT SIC code. The five-day industry adjusted reversal is measured as the compound return for the five trading days immediately prior to the last trading day before the holding period (we skip one day to minimize microstructure effects) minus the equally weighted average return over the same period for all stocks in the same two-digit COMPUSTAT SIC code.

To compute the reversal score, we first invert the percentile ranks for each of the three above measures, by subtracting that rank from the number 100. This is because we want scores to be interpreted the same way across factors: higher score, higher abnormal return potential. Thus, a stock that is a the bottom of the cross-section of returns in the previous month, would have an (un-inverted) percentile rank equal to 0, and an inverted percentile rank equal to 100, indicating significant appreciation potential in the following month due to the reversal phenomenon. A reversal score is calculated for each stock as the equal weighted inverted percentile ranks of each of the three measures.
Relative Value

Each month stocks are ranked into percentiles based upon three measures of value: Cashflow-to-Value ratio, Sales-to-Value ratio, and Book-to-Market ratio (viz., Lakonishok, Shleifer, and Vishny, 1994). A value score is calculated as the equally weighted average of the three percentile ranks corresponding to these three underlying measures.

The Cashflow-to-Value ratio is computed as the average firm cashflow over the previous twelve months, divided by the market value of the firm’s assets. This ratio is the inverse of the cashflow multiple. A high Cashflow-to-Value ratio (or low multiple) could be indicative of either underpricing, high risk, or low growth in future cashflows. Likewise, a low Cashflow-to-Value ratio (high multiple) could indicate either overpricing, low risk, or high expected growth in future cashflows. Active management takes the view that extreme values of the Cashflow-to-Value ratio are more likely to indicate mispricing rather than differences in risk or expected growth rate, especially when those differences occur among stocks within the same industry. Thus, the active manager usually takes long positions on stocks with very high Cashflow-to-Value ratios and short positions on stocks with very low Cashflow-to-Value ratios in the same industry. To compute the Cashflow-to-Value ratios, we estimate cashflow as income before extraordinary items plus depreciation and amortization. We estimate the market value of assets as the book value of assets minus book value of equity plus the market value of equity (price time shares outstanding). We then compute a 12-month Cashflow-to-Value ratio as the average of the quarterly cashflows measured over the last four quarters, divided by the by market value of assets computed using the most recently available data.

The Sales-to-Value ratio is computed in a manner identical to the Cashflow-to-Value ratio, with the only exception that the average of the four quarterly net sales data is substituted for cashflows. A higher Sales-to-Value ratio is indicative of potential underpricing.
Book-to-market is the book value of assets scaled by the market value of assets. The market value of assets is estimated as in the case of the Cashflow-to-Value ratio. A high Book-to-Market ratio could be indicative of higher risk, lower expected growth, but also underpricing. Likewise, a low Book-to-Market ratio could indicate low risk, high cashflow growth, or overpricing. Once again, active management takes the view that extreme values of the Book-to-Market ratio, especially when compared across stocks in the same industry, are more likely to be caused by mispricing rather than differences in risk or future growth rate.

Accounting Profitability

Accounting profitability is another attribute that correlates to the cross-section of stock returns. Each month we sort stocks into percentiles based upon two measures of profitability: Return on Assets (ROA) and Return on Invested Capital (ROIC). If markets are fully efficient, accounting measures of profitability should be fully incorporated into stock prices. In the presence of funding constraints, the market may underreact to the release of accounting information, and profitability could then become a predictor of future returns in the cross-section. In untabulated results we verify that sorting stocks on ROA and, respectively, on ROIC has leads to strong cross-sectional return predictability.

A profitability score is calculated as the equal-weighted average of the percentile ranks of the two underlying measures. Return on Assets is calculated as income for the most recent quarter divided by the book value of assets. Return on Invested Capital is calculated as income for the most recent quarter scaled by book value of total invested capital. Income is defined as income before extraordinary items, plus interest expense, plus minority interest.

If markets do not immediately impound profitability measures into stock prices, perhaps because of underreaction, we would expect stocks with higher profitability to earn higher future risk-
adjusted returns. In active management, a higher profitability score is indicative of underpricing (as suggested, for example, by Piotroski, 2000).

A.2. Composite AMTS Factor Construction

To be included in the base dataset, we require that a firm have valid (non-missing) observations for each of the four primary measures. In addition, to ensure sufficient liquidity for trading, each month we sort firms on prior month dollar volume of trade, and firms below the fifth percentile are dropped from the base dataset.

Security Selection

To implement the Actively Managed Trading Strategy (AMTS) we first compute a monthly composite score for each stock. The composite score is computed by adding together the four “factor” scores based on momentum, reversal, value, and profitability. Since each factor score ranges from 0 to 100, the composite score therefore ranges from 0 to 400. A security whose composite score is close to 400 is expected to significantly appreciate in value: that security has strong momentum, very low (negative) short-term returns, high accounting profitability and trades for a low multiple of cashflows. By contrast, a security whose score is close to 0 is expected to significantly depreciate in value.

The Actively Managed Trading Strategy takes long positions on stocks with unusually high composite scores and low positions on stocks with unusually low composite scores, subject to industry matching, as described in the next sub-section.

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18Consistent with industry standards, we assign equal weight to each of the four factors. For example, Credit Suisse’s CSM ETF is also designed by equally weighting the scores on the various predictive factors.
Industry Control

Long-short trading strategies such as AMTS are typically designed to eliminate exposure to market risk and take advantage of relative mispricing between securities. By construction, market neutral strategies are near zero-beta portfolios. However, a zero-beta strategy is not implementable in practice if it has high intertemporal variance. As argued in this paper, investors are reluctant to fund strategies with high volatility or large negative returns, due to the information asymmetry between investors and managers. As a result, managers attempt to minimize inter-temporal variance by matching stocks in the long and short leg of the portfolio according to risk characteristics. To ensure that AMTS is realistic and consistent with industry practice, we minimize the variance of the portfolio by matching each stock in the long leg of the portfolio with a stock in the short leg chosen from the same industry. This procedure is also consistent with academic research showing that industry adjustment better explains cross-section variation in stock returns than standard factor-based models (Johnson, Moorman, and Sorescu, 2009).

We implement our industry filter as follows. Each month, we first sort firms into industry groups based upon 2-digit SIC codes obtained from Compustat. Within each industry group, we sort firms into 30 groups based upon the value of the composite score. Group 30 in each industry contains stocks with extremely high values of the composite score, which are the most likely to be underpriced. Group 1 contains stocks with the lowest composite scores in that industry, likely to be overpriced. Within each industry, we retain only stocks in Groups 30 and 1, as candidates for the long and short position of the Actively Managed Trading Strategy. We discard stocks in Groups 2 to 29.

By matching long and short positions within each industry group, an industry-wide movement in the long position will be mostly offset by a similar movement in the short position, so the return of the long-short portfolio will primarily capture convergence toward fundamental values of securities that are subject to cross-sectional mispricing. This type of industry matching also minimizes problems related to
cross-sectional comparisons of accounting variables (such as book-to-market) which may vary widely across industries.

In some industries, the spread in composite scores between long and short positions is large. Active management takes the view that these industries are subject to higher cross-sectional inefficiencies, and higher “alpha” potential. In other industries, this spread is very low, or close to zero. In active management, a low spread is indicative of an industry where prices are relatively efficient, and the “alpha” potential is close to zero. To reduce noise in the Actively Managed Trading Strategy, we remove industries with very low composite score spreads: those where the spread between the average composite score of the long portfolio and the average composite score of the short portfolio fall in the bottom 25% of all industry spreads. These are industries without cross-sectional predictability in returns. The remaining 75% of industries display moderate-to-high cross-sectional predictability, and have higher potential to generate “alpha” in active management.

**Portfolio Formation**

Each month, long and short portfolios are formed based on the composite scoring and industry matching procedures outlined above. To ensure that AMTS captures the most recent information regarding cross-sectional mispricing, portfolios are re-formed monthly using the latest measures and held for one month. The equally weighted returns (including delisting returns) to the securities in the portfolio form the base return series used to calculate our key variables GMRET, STD, and NSTD.
Table 1: Performance of the Actively Managed Trading Strategy Net of Trading Costs: 1967-2009

Shown below are performance statistics for the monthly returns to the Actively Managed Trading Strategy, the S&P 500 index, and the 30-Day T-Bill for the period 1967 to 2009 and selected sub-periods. AMTS-Market Neutral represents returns to a long-short strategy (equal weights long and short) developed by scoring each stock on four dimensions of security mispricing: Momentum, Reversal, Value, and Profitability. Mean Net Return represents the return net of trading costs to include commissions and estimated price impact of trade. AMTS-130/70 is a long-short hedge strategy where an investor invests 130% of capital in the long leg of AMTS and 70% of the capital in the short leg of AMTS. S&P 500 represents that return to the S&P 500 index including dividends in excess of the 30-day T-Bill rate. CAPM-Alphas is the intercept from a regression of the respective portfolio’s net returns on the market model. FF3-Alphas is the intercept from a regression of the respective portfolio’s net returns on the Fama and French (1993) three factor model. The Squared Sharpe Ratio is calculated as the respective portfolio’s squared mean divided by its variance.

<table>
<thead>
<tr>
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<td>0.0009</td>
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<td>Mean Gross Return</td>
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<td>Squared Sharpe Ratio</td>
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<td>0.000</td>
<td>0.000</td>
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Table 2: Performance of Individual Components of the Actively Managed Trading Strategy

Shown below are Information Ratios and Sharpe Ratios for the monthly returns to the Actively Managed Trading Strategy and the underlying component strategies. AMTS represents the gross returns to a long-short strategy (equal weights long and short) developed by scoring each stock on four dimensions of security mispricing: Momentum (M), Reversal (R), Value (V), and Profitability (P). The strategies below represent all possible equal weighted combinations of the indicated component strategies. For example, “MV” represents a strategy where scores for each stock are computed by equally weighting the scores of the momentum and value dimensions. The Information Ratios are computed by regressing the indicated strategies on the market model and dividing the intercept by the standard deviation of the residuals. The Sharpe Ratios are computed by regressing the indicated strategies on a constant and dividing the intercept by the standard deviation of the residuals. The boxed Information and Sharpe Ratios represent the strategies at each level with the maximum value of the respective ratio. AMTS* excludes April 2009 to reduce the effects of the momentum crash of 2009 (see Daniel (2011)). T-statistics are reported in italics below the coefficient estimates, and are based on Newey-West standard errors.

<table>
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<tr>
<th>Strategy</th>
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<th>Information Ratios</th>
<th>Sharpe Ratios</th>
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<td></td>
<td>4.50</td>
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<td>3.52</td>
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<td>V</td>
<td>0.006</td>
<td>0.035</td>
<td>0.178</td>
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<td></td>
<td>0.010</td>
<td>0.029</td>
<td>0.341</td>
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<tr>
<td>P</td>
<td>0.010</td>
<td>0.029</td>
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<td></td>
<td>7.07</td>
<td></td>
<td>6.47</td>
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<tr>
<td>R</td>
<td>0.014</td>
<td>0.034</td>
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<td>0.017</td>
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<td>MV</td>
<td>0.010</td>
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<td>0.309</td>
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<td>MP</td>
<td>0.011</td>
<td>0.037</td>
<td>0.295</td>
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<td>MR</td>
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<td>VP</td>
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<td>AMTS*</td>
<td>0.020</td>
<td>0.029</td>
<td>0.699</td>
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Table 3: Summary Statistics

Shown below are summary statistics of key monthly variables measured over the periods 1967 to 2009 (in Panel A), and a richer set of variables measured during 1991 to 2009 (in Panel B). The AMTS and NSTD variables are calculated using the returns to the Actively Managed Trading Strategy (AMTS) and represent the one-month mean return and standard deviation of negative returns, respectively. NSTD is computed as the standard deviation of a modified return series calculated as min(0,daily return). MFFLOW represents the aggregate mutual fund flow scaled by beginning total net assets for funds that satisfy the following criteria: First, funds that load positively and significantly (t≥+1.96) on the AMTS factor over the prior 60-month period are classified as AMTS-compatible. Flows to those AMTS-compatible funds whose coefficients equal or exceed the cross-sectional median coefficients across all AMTS-compatible funds are aggregated to calculate MFFLOW. MFFLOWX is the aggregate mutual fund flow measure of mutual funds without a positive and significant loading on AMTS (i.e., t<+1.96). AILLIQ is an equally weighted Amihud (2002) measure of aggregate market illiquidity computed using NYSE stocks. TURN is an equally weighted aggregate turnover measure computed using NYSE stocks. RM-RF is the excess market return. LIBOR represents the 1-month LIBOR rate. TED3 represents the 3-month TED spread computed as the difference between 3-month LIBOR and 3-month T-bill interest rate. AGGIVOL is an equally-weighted aggregate idiosyncratic volatility measure computed using NYSE stocks. RETDISP is an equally-weighed cross-sectional return dispersion measure computed using large NYSE stocks (largest NYSE size decile). CRDSPRD is credit spread computed as the difference between the BAA corporate bond yield and the AAA corporate bond yield.

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<th>Variable</th>
<th>Months</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>p5</th>
<th>p25</th>
<th>P50</th>
<th>p75</th>
<th>p95</th>
<th>Max</th>
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<tbody>
<tr>
<td>AMTS</td>
<td>516</td>
<td>0.0196</td>
<td>0.0310</td>
<td>-0.1813</td>
<td>-0.0315</td>
<td>0.0037</td>
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<table>
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Table 4: Correlation of Selected Key Variables

Shown below are pairwise correlations of the key monthly variables measured over the periods 1967 to 2009 (in Panel A) and 1991 to 2009 (in panel B). The variables are defined in Table 3.

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Table 5: Mutual Fund Flows and Arbitrage Constraints

Shown below are coefficient estimates of time-series regressions over the period 1991 to 2009. The variables are defined in Table 3. The dependent variable is MFFLOW (aggregate mutual fund flow to AMTS funds) measured at time $t$. MFFLOWX (aggregate mutual fund flow to non-AMTS funds), AMTS, NSTD, RM-RF, and AILLIQ are the two-month averages of the respective variables measured over the window at $[t-2,t-1]$. In Panel A the proxies for arbitrage constraints, LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP are the two-month averages measured over the window at $[t-2,t-1]$. In Panel B, these variables are measured monthly at $(t-1)$ and $(t-2)$. T-statistics are reported in italics below the coefficient estimates, and are based on Newey-West standard errors.

Panel A: Arbitrage constraints (LIBOR, TED3, CRDSPRD, AGGIVOL, RETDISP, and TURN) are the two-month averages measured over the window at $[t-2,t-1]$

Dependent Variable: MFFLOW($t$)
Independent variables are measured as the average over the $[t-2,t-1]$ window

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49
Table 5: Mutual Fund Flows and Arbitrage Constraints (cont.)

Panel B: Arbitrage constraints (LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP) are measured monthly

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Independent variables are measured at (t-1) and (t-2)

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Table 6: Abnormal Mutual Fund Flow
Shown below are coefficient estimates of time-series regressions over the period 1991 to 2009 where the dependent variable MFLOW (aggregate flow to AMTS mutual funds) is measured at time t. The variables are defined in Table 3. The independent variables include up to six lags of MFLOW and MFLOWX (aggregate flow to non-AMTS mutual funds) and one lag of the excess market return (RM-RF) and the measure of aggregate illiquidity (AILLIQ). ABNMFFLOW(L) is estimated as the residuals of the regression specification with L lags of the flow variables. For example, ABNMFFLOW6 represents the residuals from the regression that includes 6 lags of MFLOW and MFLOWX. T-statistics are shown in italics below the coefficient estimates, and are based on Newey-West standard errors.

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Table 7: Time Series Regression Results: Future Returns to AMTS and Past Mutual Fund Flows

Shown below are coefficient estimates of time-series regressions where the dependent variable is the month \( t \) return to the Active Management Trading Strategy (“AMTS”) for the period 1991 to 2009. ABNMFFLOW6 represents the residuals from the regression specification in Table 6 that includes six lags of the MFFLOW and MFFLOWX variables. The definitions of the remaining variables are included in Table 3. The independent variables ABNMFFLOW6, MFFLOWX, RMRF, AILLIQ, and TURN are the two-month averages of the respective variables measured over the window at \([t-2,t-1]\). In Panel A the proxies for arbitrage constraints, LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP are the two-month averages measured over the window at \([t-2,t-1]\). In Panel B, these variables are measured monthly at time \((t-1)\) and \((t-2)\). Panel C replicates the analysis in Panel B, except ABNMFFLOW6 is replaced by MFFLOW further scaled by the beginning aggregate market cap of AMTS stocks (AMTSME). T-statistics are shown in italics below the coefficient estimates, and are based on Newey-West standard errors.

Panel A: Arbitrage constraints (LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP) are the two-month averages measured over the window \([t-2,t-1]\)

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Table 7: Future Returns to AMTS and Past Mutual Fund Flows (cont.)

Panel B: Arbitrage constraints (LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP) are measured monthly

Dependent Variable: AMTS(t)
Independent variables are measured monthly at time (t-1) and (t-2)

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<td>CRDSPRD (t-1)</td>
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<td>CRDSPRD (t-2)</td>
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<td>AGGIVOL (t-2)</td>
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<tr>
<td>RETDISP (t-1)</td>
<td>0.094</td>
</tr>
<tr>
<td>RETDISP (t-2)</td>
<td>-0.186</td>
</tr>
<tr>
<td>TURN (t-1)</td>
<td>-0.081 -0.090 -0.079 -0.081 -0.134 -0.064 -0.062 -0.095</td>
</tr>
<tr>
<td>TURN (t-2)</td>
<td>-0.011 -0.024 -0.026 0.003 -0.026 0.029 -0.020 0.013</td>
</tr>
<tr>
<td>MFFLOWX (t-1)</td>
<td>0.672</td>
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<tr>
<td>MFFLOWX (t-2)</td>
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<tr>
<td>RM-RF (t-1)</td>
<td>-0.103 -0.126 -0.101 -0.101 -0.083 -0.094 -0.107 -0.112</td>
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<td>RM-RF (t-2)</td>
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<td>AILLIQ (t-1)</td>
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<td>AILLIQ (t-2)</td>
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<td>Adj-R2</td>
<td>0.081 0.092 0.074 0.081 0.097 0.084 0.074 0.082</td>
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</table>
Table 8: Performance of Underlying Stocks up to 12-months

Shown below are the mean 1, 3, 6, 9 and 12-month holding period returns to AMTS stocks for the period 1991 to 2009. Each month, t-month holding period returns are computed for each stock in the AMTS portfolios which are reformed monthly. Conditional returns are computed by regressing the time t holding period returns (overlapping portfolios) onto flow variables measured at time t-2. The conditional flow dummy variables include a dummy variable equal to one if ABNMFFLOW6 is greater than or equal to zero (POSFLOW) and a dummy variable equal to one if ABNMFFLOW6 is less than zero (NEGFLOW). ABNMFFLOW6 represents the residuals from the regression specification in Table 6 that includes six lags of the MFFLOW and MFFLOWX variables. The definitions of the remaining variables are included in Table 3. T-statistics are shown in italics below the coefficient estimates, and are based on Newey-West standard errors.

<table>
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<tr>
<th></th>
<th>1M</th>
<th>3M</th>
<th>6M</th>
<th>9M</th>
<th>12M</th>
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<tr>
<td>1991-2009 NegFlow</td>
<td>0.0141</td>
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<td>4.23</td>
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<td>1991-2009 PosFlow</td>
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<td>4.00</td>
<td>4.58</td>
<td>4.02</td>
<td>5.51</td>
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Table 9: AMTS Returns and Abnormal Mutual Fund Flows: Vector Autoregressive (VAR)

Shown below are coefficient estimates of VAR regressions over the period 1991 to 2009. The variables are defined in Table 3. The endogenous variables are ABNMFFLOW6 (abnormal aggregate mutual fund flow to AMTS funds) and AMTS measured at time t. The optimal lag length is chosen by AIC criteria. T-statistics are reported in italics below the coefficient estimates, and are based on Newey-West standard errors.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Independent Variable</th>
<th>Lag</th>
<th>AMTS</th>
<th>ABNMFFLOW6</th>
<th>TURN</th>
<th>MFFLOWX</th>
<th>RM-RF</th>
<th>AILLIQ</th>
<th>INTERCEPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMTS_t</td>
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<td>t-2</td>
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<td>-0.48</td>
<td>-0.106</td>
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<td></td>
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<td>t-3</td>
<td>0.027</td>
<td>-0.349</td>
<td>0.039</td>
<td>-1.57</td>
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<td>ABNMFFLOW6_t</td>
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<td>t-2</td>
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<td>-0.014</td>
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<td>-0.47</td>
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<td></td>
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<td>-0.51</td>
<td>0.23</td>
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</table>
Table 10: Hedge Fund Flows (Market Neutral) and Capital Constraints

Shown below are coefficient estimates of time-series regressions over the period 1997 to 2009. The dependent variable is HFFLOW (aggregate hedge fund flow to AMTS hedge funds) measured at time \( t \). AMTS hedge funds are identified by regressing excess hedge fund returns (for all hedge funds with a primary strategy of market neutral) on the excess market return, AMTS, and a liquidity risk factor over the full sample period 1997 to 2009. Hedge funds with a statistically significant loading on AMTS (t-statistic >= 1.96) are classified as AMTS hedge funds. HFFLOWX (aggregate hedge fund flow to non-AMTS funds), AMTS, NSTD, and RM-RF are the two-month average of the respective variable measured over the window at \([t-2,t-1]\). The proxies for arbitrage constraints, LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP are also measured over the \([t-2, t-1]\) window. The variables are defined in Table 3. T-statistics are reported in italics below the coefficient estimates, and are based on Newey-West standard errors.

<table>
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<td>-0.009</td>
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</table>
Table 11: Time Series Regression Results: Future Returns to AMTS and Past Hedge Fund Flows

Shown below are coefficient estimates of time-series regressions where the dependent variable is the month $t$ return to the Active Management Trading Strategy ("AMTS") for the period 1997 to 2009. ABNHFFLOW6 represents the residuals from the regression specification similar to Table 6 that regress HFFLOW on six lags of the HFFLOW and HFFLOWX variables and one lag of the RM-RF and AILLIQ variables. HF and HFFLOWX are defined in Table 10. The definitions of the remaining variables are included in Table 3. The independent variables include lagged ([t-2,t-1]) measures of ABNHFFLOW6, HFFLOWX, RMRF, AILLIQ, and TURN. The proxies for arbitrage constraints, LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP are measured over the window [t-2, t-1]. T-statistics are shown in italics below the coefficient estimates, and are based on Newey-West standard errors.

Arbitrage constraints (LIBOR, TED3, CRDSPRD, AGGIVOL, and RETDISP) are the two-month averages measured over the window [t-2,t-1]

Dependent Variable: AMTS($t$)
Independent variables are measured as the average over the [t-2,t-1] window

<table>
<thead>
<tr>
<th>Variable</th>
<th>1997-2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABNHFFLOW6</td>
<td>-0.035 -0.034 -0.037 -0.034 -0.035 -0.036 -0.039 -0.037</td>
</tr>
<tr>
<td></td>
<td>-2.50 -2.55 -2.56 -2.33 -2.28 -2.58 -2.46 -2.44</td>
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<td>AMTS</td>
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<tr>
<td>NSTD</td>
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</tr>
<tr>
<td>LIBOR</td>
<td>3.422 1.82</td>
</tr>
<tr>
<td>TED3</td>
<td>0.028 2.38</td>
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<tr>
<td>CRDSPRD</td>
<td>-1.380 -1.46</td>
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<tr>
<td>AGGIVOL</td>
<td>3.028 1.66</td>
</tr>
<tr>
<td>RETDISP</td>
<td>0.263 1.16</td>
</tr>
<tr>
<td>TURN</td>
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<td>-1.74 -1.78 -2.37 -1.46 -2.95 -0.40 -2.13 -1.98</td>
</tr>
<tr>
<td>HFFLOWX</td>
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</tr>
<tr>
<td></td>
<td>1.38 1.60 2.10 0.82 0.99 1.28 1.59 1.32</td>
</tr>
<tr>
<td>RM-RF</td>
<td>-0.054 -0.109 -0.087 -0.043 0.002 -0.050 -0.014 -0.049</td>
</tr>
<tr>
<td></td>
<td>-0.82 -1.21 -1.34 -0.64 0.03 -0.73 -0.21 -0.77</td>
</tr>
<tr>
<td>AILLIQ</td>
<td>-0.186 -0.207 -0.559 -0.213 -0.461 -0.014 -1.035 -0.549</td>
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<tr>
<td>INTERCEPT</td>
<td>0.034 0.039 0.045 0.020 0.047 0.028 0.028 0.032</td>
</tr>
<tr>
<td></td>
<td>2.15 2.19 2.36 1.34 2.97 2.03 1.98 2.12</td>
</tr>
<tr>
<td>Adj-R2</td>
<td>0.024 0.025 0.044 0.036 0.075 0.030 0.047 0.027</td>
</tr>
</tbody>
</table>

Adj-R2
Table 12: AMTS Returns and Abnormal Hedge Fund Flows: Vector Autoregressive (VAR)

Shown below are coefficient estimates of VAR regressions over the period 1997 to 2009. The endogenous variables are ABNHFFLOW6 (abnormal aggregate hedge fund flow to AMTS funds) and AMTS measured at time $t$. Other variables are defined in Table 3. The optimal lag length is chosen by AIC criteria. T-statistics are reported in italics below the coefficient estimates, and are based on Newey-West standard errors.

Vector Autoregression Model Coefficient Estimates. Dependent Variables are ABNHFFLOW6 and AMTS

<table>
<thead>
<tr>
<th>Year</th>
<th>Lag</th>
<th>AMTS</th>
<th>ABNHFFLOW6</th>
<th>TURN</th>
<th>HFFLOWX</th>
<th>RM-RF</th>
<th>AILLIQ</th>
<th>INTERCEPT</th>
</tr>
</thead>
<tbody>
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<td>1997-2009</td>
<td>t-2</td>
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<td>-0.02</td>
<td>-0.146</td>
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<td>-2.12</td>
<td>0.17</td>
<td>-0.28</td>
<td>-0.77</td>
<td>2.32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year</th>
<th>Lag</th>
<th>AMTS</th>
<th>ABNHFFLOW6</th>
<th>TURN</th>
<th>HFFLOWX</th>
<th>RM-RF</th>
<th>AILLIQ</th>
<th>INTERCEPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997-2009</td>
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<td>0.019</td>
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<td>0.49</td>
<td>-0.43</td>
<td>0.61</td>
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</table>
Figure 1: Impulse Response Functions of AMTS and ABNMFFLOW6

This figure shows the response of AMTS and ABNMFFLOW6 to an impulse in AMTS and ABNMFFLOW6 up to 10 lags. The model is specified in Table 9. The middle line in each graph displays the point estimates, while the upper and lower lines display the boundaries of a 90% confidence interval.