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Capital Market Efficiency and Arbitrage Efficacy

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Abstract

Efficiency in the capital markets requires that capital flows are sufficient to arbitrage anomalies away. We examine the relation between flows to a quantitative (quant) strategy that is based on capital market anomalies and the subsequent performance of this strategy. When these flows are high, quant funds are able to implement arbitrage strategies more effectively, which in turn leads to lower profitability of market anomalies in the future, and vice versa. Thus, the degree of cross-sectional equity market efficiency varies across time with the availability of arbitrage capital.

I. Introduction

The seminal notion of market efficiency (Fama (1970)) is justified by arguing that rational traders would arbitrage away any temporary deviations of prices from efficient benchmarks. Thus, price efficiency arises through the trading actions of these arbitrageurs. Stock prices will converge to efficient benchmarks quickly when arbitrage capital is abundant, and vice versa.

In this article, we explore the premise that the availability of arbitrage capital varies over time, which results in dynamic variation in the predictability of cross-sectional stock returns. In our empirical analysis, we measure return predictability using the ex post return performance of a quantitative (quant) strategy, designed to trade on capital market anomalies documented within the academic literature

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in accounting and finance. We note that some of these anomalies earn large paper profits and have persisted out of sample long after their discovery (Bernard and Thomas (1989), Rouwenhorst (1998); see also Lee (2001), Kothari (2001), and McLean and Pontiff (2016)), indicating that it is a challenge to attribute them to data mining. Furthermore, it is difficult to come up with a risk-based story consistent with many of the anomalies documented in the literature. This suggests that cross-sectional anomalies may, at least in part, reflect temporary inefficiencies in market prices.

Based on these observations, we measure arbitrage capital using flows to mutual funds whose trades mirror those of our quant strategy (abbreviated as quant funds). To identify these quant funds, we regress the returns of all mutual funds on the returns of a quant strategy and select the funds with the highest return correlation. This correlation may arise either because quant funds directly implement quant strategies or because they employ buy-side analysts who incorporate anomaly-based information in their investment recommendations. Alternatively, the valuation models used by quant funds could identify mispriced stocks that are purchased or sold in a manner consistent with the quant strategy. In all of these cases, flows to quant funds act as a proxy for flows to arbitrage strategies where arbitrage capital is used to target temporary pricing inefficiencies and move stock prices toward efficient benchmarks.

We build on the notion that as flows to arbitrage strategies vary over time, so does the degree of capital market efficiency. Periods marked by high arbitrage flows are periods during which markets are more efficient. These periods are likely to see a correction of cross-sectional mispricing, resulting in lower returns to the quant strategy in the future. Conversely, any mispricing that is present at the beginning of periods with low arbitrage flows will likely persist throughout the period. Thus, periods marked by lower flows will be followed by periods with higher cross-sectional return predictability, which will manifest in the form of higher returns to the quant strategy.

The preceding arguments suggest the following hypothesis:

Hypothesis 1. The performance of quant strategies based on capital market anomalies is inversely related to the prior availability of arbitrage flows.

We find empirical support for the above hypothesis. Enhanced arbitrage flows to quant funds predict lower future profitability of the quant strategies and, thus, greater capital market efficiency. This finding underscores the point that market efficiency is a dynamic concept, because markets become efficient owing to intervention by arbitrageurs, whose efficacy varies over time as the availability of arbitrage capital varies.

There is a growing literature on the links between arbitrage capital and price formation. For example, in the model of Shleifer and Vishny (1997), 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 (2012), (2013), where managers' underperformance leads to capital rationing. Likewise, Pástor and Stambaugh (2012) develop a model where investors use past realized returns to infer the efficacy of quant strategies and allocate funds accordingly.[1] Vayanos (2004) shows that fund managers are unwilling to hold illiquid assets following poor performance, due to redemption risk, and Vayanos and Woolley (2013) show that investors rationally infer managers' ability from performance and withdraw capital following underperformance by fund managers. Several other papers (e.g., Acharya, Lochstoer, and Ramadorai (2013), Baker and Savasoglu (2002), Lamont and Thaler (2003), Mitchell, Pulvino, and Stafford (2002), Mitchell, Pedersen, and Pulvino (2007), and Pontiff (1996)) provide evidence supporting limits of arbitrage for different settings and markets.

Another line of research documents 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, Antón and Polk (2014), Frazzini and Lamont (2008), Jotikasthira, Lundblad, and Ramadorai (2012), Greenwood and Thesmar (2011), and Lou (2012) show that excess fund flows have large but temporary price effects. Khan, Kogan, and Serafeim (2012) provide evidence that stocks bought by mutual funds with large inflows tend to become overpriced. More recently, Kokkonen and Suominen (2015) find that hedge fund flows are negatively related to the future returns of a long–short strategy constructed using an alternative proxy for mispricing.

Our work is complementary to these papers. Specifically, we narrow our focus to flows that are directed to funds that follow arbitrage strategies and show that the main effect of these flows is to mitigate cross-sectional mispricing. We provide a direct, intertemporal empirical link between flows and the degree of capital market efficiency. Our results are robust to several alternative methodologies, including variations in the construction of the quant algorithm, the use of risk-adjusted quant returns, and the use of flows obtained from market-neutral hedge funds instead of mutual funds.

II. Data and Empirical Design

To test our hypothesis, we begin by measuring returns to arbitrage strategies. We do this at the aggregate level by constructing a quant strategy designed to trade based on common characteristics (other than market beta) that predict the cross section of stock returns. Testing our hypothesis also requires that we construct a measure of flows to quant strategy funds, as well as a set of control variables. Our sample period extends from 1991 to 2009. We begin our sample in 1991 as this is the earliest available date for mutual fund flows, a key variable in our empirical analysis.

A. Measuring Returns to the Quant Strategy

We start by simulating a quant strategy designed to trade on evidence of anomalies documented in academic research. Among the many anomalies, we select those most likely to have been known by (and acted upon by) traders early

[1] See Gromb and Vayanos (2010) for an extensive review of the theoretical literature on limits of arbitrage.

in our sample period. We do this to ensure that our strategy remains tradable throughout our sample period. This important condition stacks the cards against our hypothesis and strengthens the external validity of our findings.

To determine which characteristics were likely known by traders early in our sample, we review the literature in finance and accounting and select return predictability factors that were published in the public domain at the beginning of our sample period or during the subsequent 5 years. We identify six major return "anomalies" using this criterion: momentum, profitability, value, size, earnings, and reversal.[2] We do not include size as one of our mispricing predictors because informal discussions with money managers suggest that the prevailing consensus in the active management community is that size captures a liquidity risk (or "beta"), rather than being a mispricing characteristic (or "alpha") (see also Jacoby, Fowler, and Gottesman (2000), Berk (1995)).

The remaining five characteristics, momentum, profitability, value, earnings, and reversal, are used to simulate the quant strategy from 1991 to 2009. We include profitability, value, and reversal from the beginning of our sample. The reversal effect has been known at least since the publication of Jegadeesh's (1990) study, 1 year before the beginning of the sample period. As for the value and profitability factors, they have likely been known to investors for at least several decades, since the publication of the famed book *Security Analysis* by Graham and Dodd (1934). Momentum is added to the strategy in Jan. 1994 following publication of the original study by Jegadeesh and Titman (1993). Similarly, earnings is included in the strategy from Jan. 1997 following the publication of Sloan's study in 1996. Portfolios are formed monthly by taking long positions in stocks that appear to be undervalued and short positions in stocks that appear to be overvalued according to these three to five characteristics. To minimize the variance of the long–short strategy, we pair 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 the quant strategy.

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

B. Measuring Fund Flows

Our empirical tests are designed to measure the relation between arbitrage fund flows and future performance of the quant strategy. Our arbitrage fund selection process, described below, is designed to identify funds that are likely to trade

[2]These anomalies are documented, respectively, by Jegadeesh and Titman (1993), Rosenberg, Reid, and Lanstein (1985), Ou and Penman (1989), Basu (1977), Jaffe, Keim, and Westerfield (1989), Chan, Hamao, and Lakonishok (1991), Fama and French (1992), Bernard and Thomas (1989), Sloan (1996), and Jegadeesh (1990). There is a well-known debate on whether particular anomalies are due to risk or mispricing (Fama and French (1993), Daniel and Titman (1997), and Daniel, Hirshleifer, and Subrahmanyam (1998)). We take the position that cross-sectional predictability based on anomalies is at least in part due to mispricing.

on the cross-sectional inefficiencies identified by the quant algorithm. It is not critical that the funds we select directly employ that algorithm; our selection process can also identify funds that systematically trade, at least partially, in stocks that are most mispriced according to the quant algorithm.[3] In short, we seek to identify mutual funds that employ any investment strategy that systematically trades stocks that are mispriced according to the quant algorithm.

To compute our proxy of arbitrage fund flows, we identify a subset of mutual funds whose monthly return performance loads on the return vector of the quant strategy. The loadings are calculated using rolling 5-year regressions where excess monthly mutual fund returns are regressed on excess market returns and quant returns. To control for aggregate liquidity risk, we also include an Amihud (2002) based long–short return factor.[4] 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 nonmissing monthly flow value.

To select arbitrage funds we first regress the returns of each mutual fund on the returns of the quant strategy and focus on the loading coefficient of this regression. We then select funds whose loadings are in the top 10% of all funds. These are the funds most likely to trade on the type of cross-sectional price inefficiencies that are embedded in the construction algorithm of the quant strategy. Thus, the flows to this subset of funds are a good proxy for the arbitrage flows required by our empirical tests.

We observe that the extent to which a mutual fund does follow the quant algorithm varies significantly from one fund to another. A univariate analysis shows that the time-series average of quant loadings range from 0.169 to 1.100. The 1st and 99th percentiles values are 0.170 and 0.677, respectively, and the 5th and 95th percentile values are 0.174 and 0.511, respectively. These loadings carry an intuitive interpretation as they represent the approximate percentage of fund assets that are invested in a manner similar to the quant strategy.[5]

Although mutual funds generally take long-only positions, their trades can contribute to bringing prices toward efficiency to the extent that funds overweight stocks that are perceived to be undervalued and underweight stocks that are perceived to be overvalued by the quant algorithm.[6] Of course, not all mutual funds follow a trading strategy that mimics the quant strategy; however, to the extent

[3]This can be achieved through several indirect channels. Funds may use external analysts that incorporate the academic findings in their buy and sell recommendations. Alternatively, the funds' internal valuation models may identify mispriced stocks that are included in quant strategy. We thank the referee for making this point.

[4]The Amihud (2002) factor is constructed based on the equal-weighted return differential between the extreme deciles of portfolios sorted each month on the Amihud illiquidity measure. Although we include this factor because it is intuitive that mutual funds would be exposed to aggregate liquidity risk, our results are not very sensitive to whether this factor is included.

[5]A relevant issue is whether the loadings of mutual fund returns on quant returns exhibit stability over time, which would shed light on whether funds follow an intertemporally stable quant "style." To address this, for each quant fund selected by our procedure, we run monthly cross-sectional regressions of current loadings on their forward 36-month coefficient estimates (without an intercept). The full-sample average of this second-stage coefficient is 1.113, with a 36-lag Newey–West (1987)-corrected t-statistic of 22.7. This suggests that the coefficient estimate 36 months forward is on average about 89.8% (1/1.113) of the initial coefficient estimate, indicating reasonable intertemporal stability.

[6]As the number of funds becomes arbitrarily large, the aggregate portfolio of actively managed mutual funds resembles a two-part strategy of holding the market portfolio and holding a long

that we can (albeit imperfectly) identify 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 Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database for all existing mutual funds. We begin by computing a measure of fund flows into each of the mutual funds available in CRSP (FLOW). Similar to Huang, Wei, and Yan (2007) and Gil-Bazo and Ruiz-Verdú (2009), we compute, for 1991 to 2009, the monthly flow to mutual fund i, as follows:

$$\text{(1)} \qquad \text{FLOW}_t = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1 + \text{M\_RET}_{i,t})}{\text{TNA}_{i,t-1}},$$

where $\text{TNA}_{i,t}$ is the total net assets of mutual fund i at time t, and $\text{M\_RET}_{i,t}$ is the period return of mutual fund i at time t, net of fees.

The monthly aggregate fund flow to arbitrage strategies is computed using the $\text{FLOW}_{i,t}$ measures from funds whose monthly return-series loadings on the quant strategy are greater than or equal to the cross-sectional 90th percentile. Assuming that N mutual funds meet such criteria, we compute the aggregate flow variable as follows:

$$\text{(2)} \qquad \text{MF\_FLOW}_t = \frac{\sum_{i=1}^{N}[\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1 + \text{M\_RET}_{i,t})]}{\sum_{i=1}^{N}\text{TNA}_{i,t-1}}.$$

Throughout the remainder of the article, we suppress fund and time subscripts (i and t) from variables for notational convenience, unless necessary.

C. Control Variables

In this section we motivate our selection of control variables used for testing Hypothesis 1, the relation between quant flows and future quant performance.

1. Market Return

Our first control variable is the excess return of the aggregate stock market. Months with higher aggregate stock returns could indicate a net inflow of capital into the market. To isolate the capital that flows to arbitrage strategies, we control for excess returns, $(R_{mt} - R_{ft})$, measured as the difference in returns between the value-weighted market index and the 1-month Treasury bill (T-bill) rate at month t (obtained from Kenneth French's Web site).[7]

minus short quant strategy. The combined strategy results 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, whereas those that do not hold these stocks are not required to take a short position.

[7] See mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

2. Relative Liquidity

We also control for differences between the liquidity of stocks in the quant portfolio and the liquidity of stocks that are not in the quant portfolio. This relative liquidity measure controls for the possibility that investors might reduce trading in quant stocks during periods when these stocks are particularly illiquid, perhaps because the higher trading costs would make the quant strategies less profitable. Periods when quant stocks are relatively illiquid may also indicate that correction of mispricing may be delayed. We use two measures of aggregate liquidity. The first measure, ILLIQ_DIFF, is an aggregate measure of differences in Amihud's (2002) illiquidity measure. To compute the Amihud measure, we obtain the equal-weighted average illiquidity of stocks held in the long quant portfolio and the equal-weighted average illiquidity of stocks in the short quant portfolio. We then compute the average illiquidity of stocks in the quant portfolio as the simple average of the long and short illiquidity measures. After computing the Amihud illiquidity measure, we compute our main control variable, ILLIQ_DIFF, as the difference between the average illiquidity of stocks in the quant portfolio and the equal-weighted average illiquidity of all stocks in our sample that are not in the quant portfolios.

The second measure, TURN_DIFF, is an aggregate measure of differences in share turnover, calculated as trading volume divided by shares outstanding. We compute TURN_DIFF in the same manner as ILLIQ_DIFF, replacing illiquidity in the calculations with share turnover. It is important to note that ILLIQ_DIFF, as constructed, is a measure of illiquidity, while TURN_DIFF is a measure of liquidity. Thus, if illiquidity of quant stocks causes arbitrage strategies to be less effective, we expect future quant returns to be positively correlated with ILLIQ_DIFF and negatively correlated with TURN_DIFF.

3. Nonquant Fund Flows

To better isolate the relation between flows to quant funds and returns to the quant strategy, we control for aggregate fund flows to nonquant funds (those whose return vector loadings on the quant vector are below the 90th percentile). Assuming K nonquant funds, we compute the control variable MF_FLOW_X as follows:

$$\text{(3)} \qquad \text{MF\_FLOW\_X}_{i,t} = \frac{\sum_{i=1}^{K}[\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1+\text{M\_RET}_{i,t})]}{\sum_{i=1}^{K}\text{TNA}_{i,t-1}}.$$

4. Performance-Based Determinants of Fund Flows

There is an extensive literature that documents a flow response to recent performance (Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998)). In the spirit of this literature, we conjecture that flows to the quant strategy are also sensitive to periods of performance when recent returns to the quant strategy are negative, volatile, or both. Negative returns to the quant strategy are the result of prices diverging from their fundamental values (according to the quant algorithm). As such, periods of poor performance should lead to lower future flows to quant funds and higher performance of future quant strategies, as prices eventually converge to fundamental values. Accordingly, we construct, at the monthly level, two variables to control for constraints that are independent of fund flows:

QS_RET: The gross monthly return to the quant strategy. If investors are sensitive to performance, periods of low QS_RET may affect future flows to the quant strategy.

QS_STD: The standard deviation of the daily return to the quant strategy, computed monthly. Periods of high volatility may affect future flows to the quant strategy.

5. Marketwide Determinants of Fund Flows

Higher borrowing costs induce redemptions from arbitrage-based quant 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)).

We construct five marketwide funding constraint variables to control for marketwide effects that may affect both the performance of and flows to the quant strategy. These variables are constructed at the monthly level:

ΔLIBOR: The 1-month change in the London Interbank Offered Rate (LIBOR) obtained from Bloomberg. Higher LIBOR rates indicate higher borrowing costs, which could make it more difficult for arbitrageurs to raise the margin capital needed to trade on mispricing.

ΔTED3: The 1-month change in the TED spread (computed as the difference between the 3-month LIBOR and 3-month T-bill rates), also obtained from Bloomberg. A higher TED spread captures instances of particular illiquidity in the lending market when interbank loans command a significant premium over the Treasury rate. Again, this could increase the cost of margin capital and impede the ability of arbitrageurs to implement trades.

ΔCRD_SPRD: The 1-month change in 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 CRD_SPRD 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. Higher credit spread could also increase the cost of margin capital and impede the efficiency of arbitrage strategies.

ΔAGG_IVOL: The 1-month change in an aggregate measure of idiosyncratic volatility (computed as the equal-weighted monthly average of idiosyncratic volatility for New York Stock Exchange (NYSE) common stocks). Higher AGG_IVOL implies higher trading costs for quant strategies, because it is more difficult to find matched pairs of long and short stocks that share a similar risk profile (Pontiff (2006)). Higher AGG_IVOL also increases the probability that investors will face margin calls due to losses in other equity investments they might hold, in addition to quant strategies. Margin calls may result in forced redemptions from quant strategies to cover losses in other investments.

ΔRET_DISP: The 1-month change in an aggregate measure of return dispersion (computed as the cross-sectional standard deviation of large NYSE common stocks (largest decile)).[8] As with AGG_IVOL, higher RET_DISP indicates that arbitrage strategies are more difficult to implement, and it indicates a higher probability that investors will face margin calls in other equity investments. Again, such margin calls could cause redemptions from arbitrage strategies.

III. Descriptive Statistics

A. Historical Performance of the Quant Strategy

We begin by examining the performance of our quant strategy to assess the degree of cross-sectional efficiency in our sample. The results, presented in Table 1, are based on monthly rebalancing. However, results based on longer rebalancing periods remain qualitatively similar. Table 1 shows the gross and net returns to the quant strategy for 1975 to 2009. The net returns account for transaction costs, which include commissions as well as the price impact of trade.[9]

Quant returns are positive and significant, and remarkably persistent throughout the sample period. We divide the sample into four subperiods, each of which corresponds roughly to a different decade. In each subperiod, the quant portfolio dominates the Standard & Poor's (S&P) 500 with a lower standard deviation and higher (or equal) average return. This performance is remarkable given that the appropriate benchmark here is not the market return but the risk-free rate.[10] A long–short version of the quant strategy that invests 130% in the long quant position and 70% in the short quant position also dominates the S&P 500, in that it has lower volatility and higher returns in each subperiod.[11] Although the quant strategy is clearly not riskless, its long-term returns substantially outperform a passive investment in the S&P 500 over the sample period.

The strong performance of the quant strategy over almost four decades, even net of transaction costs, suggests an impressive level of predictability in the cross

[8]We thank Cam Harvey for suggesting this variable.

[9]Historical commissions are obtained from Jones (2002). Estimates of the price impact of trade are from Hasbrouck (2009) (http://pages.stern.nyu.edu/~jhasbrou/) using the Gibbs estimate of trading costs. These estimates assume $1 billion of assets under management in Dec. 2009. For previous years, we deflate the $1 billion amount using the value-weighted market index (including dividends) obtained from CRSP.

[10]Because the quant strategy 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&P 500 to illustrate the extraordinary performance of this strategy over several decades.

[11]This strategy is referred to as "130/70" in the industry. It is designed to take advantage of potential cross-sectional inefficiencies while allowing participation on the long side of the market ($60 net long) to earn the long-term equity premium.

TABLE 1

Performance of the Academic-Anomaly-Based Quantitative Strategy (1975–2009)

Table 1 reports the performance statistics for the monthly returns to the quantitative strategy (QS) based on academic anomalies, the Standard & Poor's (S&P) 500 index, and the 30-day Treasury bill (T-bill) for 1975 to 2009 and selected subperiods. QS-market neutral represents returns to a long–short strategy (equal weights long and short) developed by scoring each stock on 5 dimensions of security mispricing: momentum, reversal, value, earnings, and profitability. Mean net return represents the return net of trading costs to include commissions and estimated price impact of trade. QS-130/70 is a long–short hedge strategy where an investor invests 130% of capital in the long leg of QS and 70% of the capital in the short leg of QS. S&P 500 represents the return to the S&P 500 index including dividends in excess of the 30-day T-bill rate. Capital asset pricing model (CAPM) alpha is the intercept from a regression of the respective portfolio's net returns on the market model. FF3 alpha is the intercept from a regression of the respective portfolio's net returns on the Fama–French (1993) 3-factor model. The squared Sharpe ratio is calculated as the respective portfolio's squared mean divided by its variance.

Portfolios	Performance Measure	1975–2009	1975–1979	1980–1989	1990–1999	2000–2009
S&P 500 (excess return)	Mean return	0.0057	0.0070	0.0076	0.0108	−0.0020
	t-statistic	(2.46)	(1.33)	(1.77)	(3.71)	(−0.38)
	CAPM alpha	0.0000	−0.0018	0.0010	0.0009	−0.0012
	t-statistic	(0.03)	(−2.16)	(1.91)	(1.27)	(−2.18)
	FF3 alpha	0.0003	0.0004	0.0008	0.0004	−0.0005
	t-statistic	(1.61)	(0.83)	(2.52)	(1.07)	(−0.96)
	Squared Sharpe ratio	0.0164	0.0278	0.0250	0.0774	0.0018
	p-value	(0.009)	(0.205)	(0.087)	(0.003)	(0.646)
30-day T-bill	Mean return	0.0046	0.0054	0.0071	0.0040	0.0023
	t-statistic	(12.79)	(11.08)	(14.91)	(17.28)	(6.66)
QS-market neutral	Mean gross return	0.0185	0.0243	0.0257	0.0167	0.0101
	t-statistic	(9.83)	(9.10)	(10.16)	(6.89)	(2.46)
	Mean net return	0.0148	0.0147	0.0216	0.0144	0.0086
	t-statistic	(8.11)	(5.28)	(8.46)	(5.80)	(2.04)
	CAPM alpha (net)	0.0153	0.0144	0.0213	0.0139	0.0083
	t-statistic	(9.11)	(5.28)	(8.00)	(5.24)	(2.14)
	FF3 alpha (net)	0.0158	0.0141	0.0218	0.0140	0.0088
	t-statistic	(10.52)	(5.13)	(7.69)	(5.62)	(2.38)
	Squared Sharpe ratio	0.2650	0.4757	0.8284	0.3827	0.0493
	p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)
QS-130/70	Mean gross return	0.0260	0.0377	0.0345	0.0239	0.0138
	t-statistic	(10.32)	(6.96)	(8.55)	(6.96)	(2.90)
	Mean net return	0.0204	0.0260	0.0273	0.0197	0.0114
	t-statistic	(8.74)	(4.86)	(6.85)	(5.76)	(2.38)
	CAPM alpha (net)	0.0167	0.0181	0.0222	0.0123	0.0117
	t-statistic	(8.86)	(7.85)	(8.12)	(4.53)	(2.69)
	FF3 alpha (net)	0.0158	0.0139	0.0231	0.0128	0.0098
	t-statistic	(10.24)	(5.53)	(8.43)	(4.49)	(2.71)
	Squared Sharpe ratio	0.2360	0.3362	0.3869	0.2696	0.0765
	p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)

section of U.S. stock returns. This performance is particularly puzzling during the most recent decade, given the large number of funds that actively trade on these factors, as well as the vast amount of information (especially from academic research) available to fund managers about cross-sectional return predictability. Our article suggests that cross-sectional predictability may persist because arbitrage flows may vary over time.

Table 2 provides summary statistics of our key variables over the period corresponding to the availability of mutual fund data (1991 to 2009). Panel A provides univariate statistics and Panel B provides pairwise correlations between the key variables. The correlation between QS_RET and QS_STD is negative, suggesting that periods of high volatility also correspond to lower contemporaneous returns to the quant strategy. We observe that QS_RET and QS_STD are both

TABLE 2

Summary Statistics

Panel A of Table 2 reports the descriptive statistics and Panel B reports the pairwise correlations of key monthly variables measured from 1991 to 2009. QS_RET and QS_STD are calculated using the returns to the quantitative strategy (QS) and represent the 1-month mean return and 1-month standard deviation of daily QS returns, respectively. MF_FLOW represents the aggregate mutual fund flow scaled by beginning total net assets for funds that load on the QS factor over the prior 60-month period with coefficient estimates above the 90th percentile. MF_FLOW_X is the aggregate mutual fund flow measure of mutual funds that are not included in MF_FLOW. ILLIQ_DIFF is an Amihud (2002) measure computed as the equal-weighted average illiquidity of stocks included in the QS strategy minus the equal-weighted average illiquidity of the stocks that are not included in the measure. TURN_DIFF is computed in a similar manner as the difference in equal-weighted aggregate turnover measures between stocks that are included in the QS strategy and those that are not. $R_m - R_f$ is the excess market return. ΔLIBOR represents the 1-month change in the 1-month London Interbank Offered Rate. ΔTED3 represents the 1-month change in the 3-month ΔTED spread computed as the difference between 3-month LIBOR and 3-month Treasury bill (T-bill) interest rate. ΔCRD_SPRD is the 1-month change in credit spread, which is computed as the difference between the BAA corporate bond yield and the AAA corporate bond yield. ΔAGG_IVOL is the 1-month change in an equal-weighted aggregate idiosyncratic volatility measure computed using New York Stock Exchange (NYSE) stocks. ΔRET_DISP is the 1-month change in an equal-weighted cross-sectional return dispersion measure computed using large NYSE stocks (largest NYSE size decile).

Panel A. Descriptive Statistics (1991–2009)

Variables	No. of Months	Mean	SD	Min	P5	P25	P50	P75	P95	Max
QS_RET	228	0.0124	0.0320	−0.1734	−0.0326	−0.0029	0.0139	0.0313	0.0552	0.1416
QS_STD	228	0.0055	0.0025	0.0021	0.0031	0.0039	0.0048	0.0062	0.0107	0.0185
MF_FLOW	228	0.0064	0.0088	−0.0239	−0.0080	0.0010	0.0066	0.0115	0.0202	0.0285
MF_FLOW_X	228	0.0030	0.0066	−0.0129	−0.0066	−0.0016	0.0028	0.0066	0.0131	0.0344
TURN_DIFF	228	0.0204	0.0284	−0.0277	−0.0116	0.0055	0.0148	0.0272	0.0716	0.2055
ILLIQ_DIFF	228	0.0017	0.0072	−0.0199	−0.0033	0.0000	0.0002	0.0009	0.0116	0.0727
$R_m - R_f$	228	0.0055	0.0443	−0.1855	−0.0774	−0.0216	0.0105	0.0348	0.0710	0.1105
ΔLIBOR	228	0.0000	0.0003	−0.0012	−0.0005	−0.0001	0.0000	0.0001	0.0003	0.0012
ΔTED3	228	−0.0035	0.2460	−0.8274	−0.3291	−0.0962	−0.0190	0.0956	0.2545	2.0477
ΔCRD_SPRD	228	0.0000	0.0012	−0.0063	−0.0011	−0.0004	−0.0001	0.0003	0.0012	0.0094
ΔAGG_IVOL	228	0.0000	0.0025	−0.0085	−0.0040	−0.0011	−0.0001	0.0011	0.0036	0.0132
ΔRET_DISP	228	0.0000	0.0188	−0.0639	−0.0268	−0.0113	−0.0003	0.0106	0.0311	0.0837

Panel B. Pairwise Correlations (1991–2009)

Variables	QS_RET	QS_STD	MF_FLOW	MF_FLOW_X	TURN_DIFF	ILLIQ_DIFF	$R_m - R_f$	ΔLIBOR	ΔTED3	ΔCRD_SPRD	ΔAGG_IVOL
QS_STD	−0.166										
MF_FLOW	−0.076	−0.346									
MF_FLOW_X	−0.075	0.092	0.122								
TURN_DIFF	−0.135	0.303	−0.179	−0.115							
ILLIQ_DIFF	−0.003	−0.052	−0.025	0.038	−0.072						
$R_m - R_f$	−0.274	−0.164	0.328	0.066	−0.134	−0.055					
ΔLIBOR	−0.040	−0.266	0.116	−0.203	0.015	−0.008	0.011				
ΔTED3	−0.003	−0.060	−0.114	−0.180	0.168	0.028	−0.156	0.498			
ΔCRD_SPRD	0.129	0.218	−0.339	0.093	0.126	−0.001	−0.235	−0.202	0.019		
ΔAGG_IVOL	0.093	0.177	−0.133	0.001	0.196	−0.044	−0.138	−0.094	0.184	0.270	
ΔRET_DISP	0.043	−0.009	0.091	−0.063	0.091	−0.099	0.061	−0.011	0.166	0.044	0.400

negatively correlated with $R_{mt} - R_{ft}$, indicating that aggregate market returns can affect the degree of market efficiency.

B. Relation between Performance and Flows

Before we proceed to a formal test of our main hypothesis (Hypothesis 1), we examine the relation between the performance of the quant strategy and future flows to quant mutual funds. Although a positive relation between performance and flows has been documented in a more general context (Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998)), we are interested in determining whether this relation extends to the specific case of arbitrage flows and quant funds.

We conjecture that prior negative performance of quant strategies will impede future flows to quant funds. The results are presented in Table 3, where the quant flows are measured at time t (MF_FLOW$_t$), and past performance is measured during $[t-3, t-1]$. Column 1 examines the relation between past performance and future flows. Consistent with our conjecture, we find that the coefficient on QS_RET is positive and significant with an estimate of 0.075 (t-statistic $= 2.22$) for 1991 to 2009.

TABLE 3

Mutual Fund Flows and Arbitrage Constraints

Table 3 reports the coefficient estimates of time-series regressions from 1991 to 2009. The variables are defined in Table 2. The dependent variable is MF_FLOW (aggregate mutual fund flow to quantitative strategy (QS) funds) measured at time t. MF_FLOW_X (aggregate mutual fund flow to non-QS funds), QS_RET, QS_STD, and $R_m - R_f$ are the 3-month averages of the respective variables measured over the window at $[t-3, t-1]$. The t-statistics are reported in parentheses below the coefficient estimates and are based on the Newey–West (1987) standard errors.

Variables	1	2	3
QS_RET	0.075		0.047
	(2.22)		(1.16)
QS_STD		−0.819	−0.658
		(−2.15)	(−1.34)
MF_FLOW_X	−0.001	0.097	0.047
	(−0.01)	(0.63)	(0.30)
$R_m - R_f$	0.097	0.063	0.076
	(3.19)	(2.83)	(2.51)
Intercept	0.005	0.010	0.009
	(4.17)	(4.38)	(2.88)
Adj. R^2	0.083	0.095	0.099

Column 2 in Table 3 shows the relation between the volatility of the quant strategy measured during $[t-3, t-1]$ and future quant flows. If credit is rationed as a result of high volatility, we expect this relation to be negative. The results support this conjecture: The coefficient of the volatility variable (QS_STD) is negative and significant with an estimate of -0.819 (t-statistic $= -2.15$).

In column 3 of Table 3 we include both the return and volatility variables. Although the coefficients on QS_RET and QS_STD are now insignificant, they preserve their signs (positive and negative, respectively). The lack of significance of the individual coefficients is due to the strong negative correlation between them (p-value $= 0.0001$). An F-test corroborates this conjecture: The coefficients of QS_RET and QS_STD are jointly significant at the 5% level (p-value $= 0.0182$). Together, these results support the notion that poor past performance and high volatility both lead to lower future quant flows.

In columns 1–3 of Table 3, the coefficient on MF_FLOW_X, the flow to nonquant funds, is insignificant. The coefficient on the market term ($R_m - R_f$) is positive and strongly significant, suggesting that investors are more likely to allocate money to quant strategies following strong market performance.

IV. The Effect of Flows on Future Anomaly-Based Returns

We now perform a formal test of Hypothesis 1 by examining the relation between quant flows and the future performance of the quant strategy. We propose that high quant flows make it easier for quant funds to arbitrage mispriced stocks and reestablish market efficiency, resulting in less cross-sectional predictability and lower quant returns in the future, and vice versa.

A. Abnormal Flows to Quant Funds

Our base variable, MF_FLOW, measures flows into funds with loadings on the quant strategy that are in the top 10% of loadings in the cross section of funds. However, from an intertemporal perspective, aggregate fund flows increase significantly over the sample period, and changes in MF_FLOW could capture effects of aggregate flow increases, in addition to capturing variation in arbitrage capital. Specifically, the aggregate assets of mutual funds in our data set increased from $865 billion to $9.7 trillion during our sample period from 1991 to 2009, and MF_FLOW does not account for this significant temporal trend.

To control for the effect of aggregate flows, we use abnormal fund flows (rather than raw fund flows) to explain the future profitability of the quant strategy. Our abnormal flow variable, ABN_MF_FLOW6, captures flows to quant funds, net of trends in aggregate flows (to both quant and nonquant funds). We also control for flows that may be related to aggregate market returns. ABN_MF_FLOW6 is measured as the residuals obtained by regressing MF_FLOW on past flows and controls, according to the following specification:

$$\text{(4)} \quad \text{MF\_FLOW}_t = a + \sum_{i=1}^{6} b_{1,i}\text{MF\_FLOW}_{t-i} + \sum_{i=1}^{6} b_{2,i}\text{MF\_FLOW\_X}_{t-i} + b_3(\text{R}_{mt-1} - \text{R}_{ft-1}) + e_t.$$

The ABN_MF_FLOW6 measure captures innovations in flows to quant funds that are not related to changes in the aggregate level of fund flows.

B. Relation between Abnormal Fund Flows and Future Quant Returns

Returns to the quant strategy result from the convergence of cross-sectional stock prices toward fundamental values (as determined by the quant algorithm) during the month the returns are measured. These returns are determined by the level of mispricing at the beginning of each month and by the extent to which prices converge to fundamental values during the month. Cross-sectional predictability is a function of the flow to arbitrage strategies in prior periods. Specifically, when arbitrage capital flows freely, prices will more closely reflect fundamental values, resulting in relatively less cross-sectional mispricing and lower quant returns in the future. Thus, according to Hypothesis 1, we expect a negative relation between flows to quant funds and future quant returns.

We now provide a formal test of Hypothesis 1. Specifically, we seek to detect a negative relation between ABN_MF_FLOW6 (our measure of abnormal flows to quant funds) and future returns to the quant strategy (our proxy for cross-sectional return predictability). The results are presented in Table 4, where monthly returns to the quant strategy (QS_RET) are regressed on lagged abnormal flows to quant funds (ABN_MF_FLOW6). We also include measures of capital constraints and

TABLE 4

Time-Series Regression Results:
Future Returns to the Quantitative Strategy and Past Mutual Fund Flows

Table 4 reports the coefficient estimates of time-series regressions where the dependent variable is the month t return to the quantitative strategy (QS) for 1991 to 2009. ABN_MF_FLOW6 represents the residuals from the regression of MF_FLOW on 6 lags of the MF_FLOW and MF_FLOW_X variables and 1 lag of the $R_m - R_f$ variable. The definitions of the remaining variables are included in Table 3. The independent variables ABN_MF_FLOW6, MF_FLOW_X, $R_m - R_f$, ILLIQ_DIFF, and TURN_DIFF are the 3-month averages of the respective variables measured over the window at $[t-3, t-1]$. The proxies for arbitrage constraints, ΔLIBOR, ΔTED3, ΔCRD_SPRD, ΔAGG_IVOL, and ΔRET_DISP are defined in Table 2. The t-statistics are shown in parentheses below the coefficient estimates and are based on the Newey–West (1987) standard errors.

	1991–2009								
Variables	1	2	3	4	5	6	7	8	9
ABN_MF_FLOW6	−1.458	−1.455	−1.530	−1.526	−1.475	−1.309	−1.341	−1.354	−1.452
	(−3.47)	(−3.59)	(−3.51)	(−3.48)	(−3.54)	(−3.35)	(−3.39)	(−3.50)	(−3.43)
QS_RET		0.076		0.024					
		(0.51)		(0.18)					
QS_STD			−1.555	−1.496					
			(−0.89)	(−0.84)					
ΔLIBOR					−3.510				
					(−0.23)				
ΔTED3						0.032			
						(2.04)			
ΔCRD_SPRD							5.003		
							(1.63)		
ΔAGG_IVOL								2.798	
								(1.63)	
ΔRET_DISP									−0.052
									(−0.09)
MF_FLOW_X	1.680	1.658	1.788	1.777	1.607	1.765	1.335	1.586	1.686
	(2.04)	(2.06)	(2.08)	(2.05)	(1.80)	(2.03)	(1.72)	(1.94)	(2.04)
TURN_DIFF	−0.233	−0.208	−0.193	−0.187	−0.237	−0.243	−0.252	−0.249	−0.232
	(−2.13)	(−1.92)	(−1.83)	(−1.63)	(−2.24)	(−2.45)	(−2.32)	(−2.29)	(−2.09)
ILLIQ_DIFF	0.370	0.349	0.343	0.338	0.363	0.328	0.397	0.310	0.366
	(1.00)	(0.94)	(0.92)	(0.89)	(0.96)	(0.88)	(1.02)	(0.83)	(0.98)
$R_m - R_f$	0.150	0.169	0.122	0.129	0.155	0.165	0.214	0.183	0.148
	(2.51)	(2.07)	(2.49)	(2.03)	(2.51)	(2.89)	(2.02)	(2.75)	(2.45)
Intercept	0.011	0.009	0.018	0.018	0.011	0.011	0.012	0.011	0.011
	(2.79)	(1.73)	(2.34)	(1.92)	(2.76)	(2.76)	(3.35)	(3.05)	(2.78)
Adj. R^2	0.098	0.096	0.103	0.099	0.094	0.107	0.108	0.102	0.094

control variables described in Section II. We expect that flows to quant funds will affect the performance of the quant strategy with a time lag (as abnormal fund flows may be invested with a delay). We have no priors as to the length of the lag, but instead allow the time-series properties of the data to determine the appropriate window. In untabulated results, we compute the Akaike information criterion (AIC) and Bayesian information criterion (BIC) measures for windows that extend from 1 to 12 months, and both measures suggest that the appropriate length of the window is 3 months. Accordingly, the independent variables are measured with a lag over a 3-month period $[t-3, t-1]$.

As conjectured, the relation between abnormal mutual fund flows (ABN_MF_FLOW6) and future quant returns (QS_RET) is negative and significant for all empirical specifications, suggesting that cross-sectional efficiency is weaker when flows to quant strategies are restricted. Interestingly, the coefficients of MF_FLOW_X are positive and significant, suggesting that cross-sectional efficiency is also weaker following periods when flows to nonarbitrage funds are unusually high.

The coefficient on the excess market return ($R_m - R_f$) is positive and significant for all specifications, suggesting that periods of high market returns lead to more mispricing in the cross section and higher future quant returns. The coefficient estimate on the relative turnover measure (TURN_DIFF) is negative and significant in all specifications, suggesting that periods of relatively lower liquidity for quant stocks are followed by higher levels of cross-sectional mispricing. This is corroborated by the coefficient estimate on relative illiquidity (ILLIQ_DIFF) that, although insignificant, carries the correct, positive sign.

The positive and significant relation between the change in TED spread and future returns to the quant strategy suggests that increased illiquidity in the bond market is associated with higher cross-sectional mispricing in the equity market, perhaps because of the higher cost of raising margin capital. The coefficients on changes in credit spread and changes in aggregate idiosyncratic volatility are marginally significant and carry the correct positive sign. Higher credit spreads can impede cross-sectional efficiency in the stock market by raising the cost of margin capital. Conversely, higher idiosyncratic volatility impedes efficiency by increasing the difficulty of forming an arbitrage-free quant portfolio.

The two performance constraint variables (QS_RET and QS_STD) that are significant in Table 3 are not significant in the presence of abnormal fund flows (ABN_MF_FLOW6). These two constraints do not appear to impede market efficiency beyond the effect that operates through the fund flow measure.

In terms of economic significance, the (untabulated) standard deviation of ABN_MF_FLOW6 is 0.0042. When we multiply the coefficient of ABN_MF_FLOW6 in Table 4 (typically −1.45) by 0.0042, we find that a 1-standard-deviation increase in ABN_MF_FLOW6 implies a decrease in the quant returns of 0.61% per month, or 7.3% per year, which is material.

We also estimate a vector autoregression (VAR) system (untabulated) to better understand the joint dynamics of the quant strategy returns and abnormal fund flows. We find a negative and significant relation between quant strategy returns and the second lag (−0.691, t-statistic = −2.16) and third lag (−0.669, t-statistic = −2.15) of abnormal fund flows. By contrast, there seems to be no relation between abnormal fund flows and lagged values of quant strategy returns.

Overall, the results presented in this section provide strong support for Hypothesis 1: Future quant returns are negatively and significantly related to abnormal flows to the quant strategy.

V. Robustness Tests

We now conduct a series of tests to assess the robustness of our results under different assumptions and empirical specifications.

A. Alternative Construction of the Quant Strategy

We first explore several variations to the list of predictability factors used in the construction of our quant strategy. Recall that in our main tests presented in Table 4, the quant strategy uses the value, profitability, and reversal factors from the beginning of our sample, the momentum factor from Jan. 1994 and the earnings factor from Jan. 1997. This algorithm was chosen to ensure that the predictive factors were known by investors (or at least knowable) at the time the returns to the quant strategy were measured. This algorithm is admittedly imperfect because it is difficult to determine in retrospect the exact date each factor became knowable to the investment community. For this reason, we explore three plausible alternative specifications for the factor selection algorithm of the quant strategy.

The first specification includes all 5 factors from the beginning of the sample. The assumption here is that the predictability power of earnings and momentum was known to investors about 5 years before the respective academic studies were published. The second specification addresses the concern that trading on the earnings anomaly may not be as widespread as the other anomalies and thus excludes that factor from the construction of the quant strategy.[12] The third specification delays the inclusion of the momentum and earnings subfactors for an additional 5 years after publication (Jan. 1999 and Jan. 2002, respectively).

The results are presented in Table 5. For each alternative specification, we repeat the analysis from the first column of Table 4. Once again, our results are robust to these alternative specifications. The coefficient estimate on abnormal flows is negative and significant in each case.

TABLE 5

Robustness: Alternative Specifications for the Quantitative Strategy

Table 5 reports the coefficient estimates of time-series regressions where the dependent variables are month t returns to alternative specifications of the quantitative strategy (QS) for 1991 to 2009. Descriptions of each alternative specification are provided briefly above each column and in more detail within the text. ABN_MF_FLOW6 represents the residuals from the regression of the respective MF_FLOW on 6 lags of the MF_FLOW and MF_FLOW_X variables and 1 lag of the $R_m - R_f$ variable. The definitions of the remaining variables are included in Table 3. The independent variables ABN_MF_FLOW6, MF_FLOW_X, $R_m - R_f$, ILLIQ_DIFF, and TURN_DIFF are the 3-month averages of the respective variables measured over the window at $[t-3, t-1]$. The t-statistics are reported in parentheses below the coefficient estimates and are based on the Newey–West (1987) standard errors.

	Description of Alternative Specifications of QS (1991–2009)		
Variables	All 5 Factors Included for Full Sample	Earnings Factors Excluded for Full Sample	Lag Inclusion of Factors by 5 Years after Publication
ABN_MF_FLOW6	−1.418	−1.364	−1.151
	(−2.91)	(−2.61)	(−2.18)
MF_FLOW_X	1.682	1.797	1.544
	(2.20)	(2.02)	(1.84)
TURN_DIFF	−0.229	−0.053	−0.239
	(−2.17)	(−0.46)	(−2.15)
ILLIQ_DIFF	0.166	0.237	0.346
	(0.47)	(0.71)	(1.03)
$R_m - R_f$	0.145	0.156	0.137
	(2.31)	(2.59)	(1.65)
Intercept	0.011	0.006	0.012
	(2.93)	(1.10)	(2.98)
Adj. R^2	0.087	0.048	0.067

B. Alternative Specifications for Identifying Quant Mutual Funds

We now explore several variations to the method used to identify the quant mutual funds, which are the funds included in the computation of abnormal fund

[12]This conclusion is corroborated through informal interviews with quantitative analysts in the industry, conducted through the Chicago Quantitative Alliance.

flows to the quant strategy (ABN_MF_FLOW6). Although our main results in Table 4 are based on the 10% of mutual funds whose returns have the highest loading on the return to the quant strategy, we explore four alternative specifications for selecting the quant funds.

The first specification retains funds with return loadings on the quant strategy that are in the top 20% (as opposed to 10%) of all funds. The second specification retains funds with return loadings that are both in the top 20% and significant at the 10% level. The third specification retains funds with return loadings that are both in the top 10% and significant at the 10% level. The fourth specification retains the top half of the funds whose loadings are significant at the 5% level.

For each alternative specification we repeat the analysis from the first column of Table 4 (untabulated). Our results are robust to all four alternative specifications used to identify quant funds. Coefficient estimates on abnormal flows remain negative and significant in all cases, ranging from −0.849 to −1.716 (t-statistics = −2.16 to −3.04).

C. 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 they do not own. Arguably, aggregate flows to hedge funds provide a better measure of arbitrage capital when compared to aggregate flows to mutual funds. However, using hedge fund data to measure aggregate flows imposes several important limitations because of well-documented biases (e.g., selection and survivorship bias) and because most databases cover a limited number of years and limited number of hedge funds whose collective flows might not be representative of the aggregate flows. It is because of these limitations that we use mutual fund flows for our main analysis in Table 4.

For robustness, we repeat our analysis using hedge fund flows as a proxy for flows to the quant strategy. We obtain flows to market-neutral hedge funds from the HedgeFund.net database. The data begin in 1997. We chose market-neutral hedge funds because these funds (like our quant strategy) are specifically designed to take advantage of cross-sectional mispricing with minimal exposure to the stock market factor.

Table 6 repeats the analysis of Table 4, substituting abnormal mutual fund flows with abnormal hedge fund flows (ABN_HF_FLOW6). As is the case with mutual fund flows, hedge fund flows increase significantly through time. To control for this trend in aggregate flows, we again use abnormal fund flows (rather than raw fund flows) to explain the future profitability of the quant strategy. Abnormal flows for hedge funds are computed in a manner similar to abnormal mutual fund flows. ABN_HF_FLOW6 is measured as the residuals obtained by regressing HF_FLOW on past flows and controls, according to the following specification:

$$\text{HF\_FLOW}_t \quad = \quad a + \sum_{i=1}^{6} b_{1,i}\text{HF\_FLOW}_{t-i} + b_2(\text{R}_{mt-1} - \text{R}_{ft-1}) + e_t.$$

TABLE 6

Robustness: Future Returns to Quantitative Strategy and Past Hedge Fund Flows

Table 6 reports the coefficient estimates of time-series regressions where the dependent variable is the month t return to the quantitative strategy (QS) for 1997 to 2009. ABN_HF_FLOW6 represents the residuals from the regression of HF_FLOW on 6 lags of the HF_FLOW and 1 lag of the $R_m - R_f$ variable. The construction of ABN_HF_FLOW is defined in Section V.C. The definitions of the remaining variables are included in Table 3. The independent variables include lagged ([$t-3$, $t-1$]) measures of ABN_HF_FLOW6, HF_FLOW_X, $R_m - R_f$, ILLIQ_DIFF, and TURN_DIFF. The proxies for arbitrage constraints, ΔLIBOR, ΔTED3, ΔCRD_SPRD, ΔAGG_IVOL, and ΔRET_DISP are defined in Table 2. t-statistics are reported in parentheses below the coefficient estimates, and are based on the Newey–West (1987) standard errors.

	1997–2009								
Variables	1	2	3	4	5	6	7	8	9
ABN_HF_FLOW6	−0.030	−0.031	−0.030	−0.030	−0.032	−0.029	−0.033	−0.026	−0.031
	(−3.59)	(−3.57)	(−3.12)	(−3.04)	(−3.54)	(−3.09)	(−3.78)	(−3.44)	(−3.58)
QS_RET		0.080		−0.015					
		(0.38)		(−0.11)					
QS_STD			−1.499	−1.550					
			(−0.77)	(−0.81)					
ΔLIBOR					−19.233				
					(−1.22)				
ΔTED3						0.033			
						(1.85)			
ΔCRD_SPRD							8.007		
							(2.68)		
ΔAGG_IVOL								3.352	
								(1.55)	
ΔRET_DISP									−0.047
									(−0.08)
TURN_DIFF	−0.204	−0.182	−0.163	−0.166	−0.221	−0.225	−0.251	−0.239	−0.202
	(−1.68)	(−1.43)	(−1.23)	(−1.16)	(−1.80)	(−2.06)	(−2.45)	(−1.98)	(−1.60)
ILLIQ_DIFF	10.931	10.024	12.163	12.379	9.466	10.490	7.378	8.407	11.037
	(2.19)	(2.39)	(2.00)	(1.97)	(1.61)	(2.39)	(2.04)	(2.20)	(2.01)
$R_m - R_f$	0.094	0.119	0.062	0.056	0.126	0.117	0.222	0.146	0.093
	(1.85)	(1.54)	(0.94)	(0.70)	(2.07)	(2.43)	(2.04)	(2.50)	(1.86)
Intercept	0.013	0.012	0.020	0.021	0.013	0.013	0.014	0.014	0.013
	(3.25)	(1.91)	(2.52)	(2.56)	(2.97)	(3.98)	(4.40)	(3.96)	(2.97)
Adj. R^2	0.048	0.042	0.051	0.044	0.049	0.057	0.083	0.053	0.041

The results are very similar to those obtained with mutual fund flows in Table 4. Abnormal hedge fund flows are negatively and significantly related to future quant returns, with coefficient estimates ranging from −0.026 to −0.031 (t-statistics = −3.04 to −3.78). Moreover, the proxies for funding constraints that were significant in Table 4 continue to be significant here: ΔTED3 (t-statistic = 1.85) and ΔCRD_SPRD (t-statistic = 2.68). The coefficient of ΔAGG_IVOL remains positive but does not attain statistical significance at conventional levels (t-statistic = 1.55). Finally, the two liquidity measures TURN_DIFF and ILLIQ_DIFF always carry the correct signs (negative and positive, respectively) and are generally significant.

We also examine whether one proxy of arbitrage capital subsumes the other. We repeat the analysis in Table 6 (untabulated) including both abnormal hedge fund flows and abnormal mutual fund flows (to quant funds) in each of the regression specifications. Coefficient estimates on the abnormal mutual fund flow variable range from −1.058 to −1.389 (t-statistics = −2.17 to −2.63), and coefficient estimates on the abnormal hedge fund flow variable range from −0.021 to −0.028 (t-statistics = −2.43 to −3.14). Although there is a slight attenuation in the magnitude of the coefficient estimates for both variables, the relation between both proxies of arbitrage capital and future quant strategy returns remains negative and significant.

Overall, we conclude from Table 6 that our results are robust to the use of flows to market-neutral hedge funds as a proxy for arbitrage capital.

D. Risk-Adjusted and Detrended Quant Returns

We conduct two final robustness tests. First, we repeat the analysis in Table 4 with a risk-adjusted measure of quant returns, constructed as the raw return to the quant strategy (QS_RET) minus the expected value of QS_RET obtained from a market model estimated over 60-month rolling windows. Although the quant strategy is a long–short strategy designed to have a beta of 0, we include the market factor ($R_m - R_f$) 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 4, indicating that the relation between abnormal flows and quant returns is not explained by the market risk factor.

Second, we detrend the return to the quant strategy (QS_RET) to ascertain that our results are not due to a time trend in that variable (e.g., decrease in the magnitude of various anomalies over time). Consistent with the results of Table 4, the coefficient estimates on the abnormal flow measures (untabulated) remain negative and significant at the 1% level.

VI. Alternative Explanation: The Dumb Money Hypothesis

The main empirical result in this article (the negative relation between fund flows and future quant returns) is clearly consistent with the notion that an increased flow of arbitrage capital enhances cross-sectional market efficiency and vice versa; we call this a phenomenon induced by "limits to arbitrage." In this section we investigate whether this result is consistent with an alternative explanation: the "dumb money" effect documented by Frazzini and Lamont (2008).

The dumb money effect refers to the tendency of unsophisticated investors to chase fund performance. If fund managers are equally unsophisticated and happen to invest new fund flows into existing stock holdings (see, e.g., Ben-Rephael, Kandel, and Wohl (2012)), then any new flows will cause stocks in the long leg of the quant strategy to become overvalued. Over the longer term, this mispricing induced by new flows will correct and the prices of stocks in the long leg of the quant strategy will revert to fundamental values. When this reversal occurs, the quant strategy delivers a negative performance. Thus, a negative relation between flows and quant returns appears to also be consistent with a dumb money explanation, at least on a prima facie basis.

Despite the apparent similarity in empirical predictions, the limits-to-arbitrage and dumb money explanations are not observationally equivalent and can be distinguished from each other through additional empirical analysis. We should first note that the underlying economics are different across the two explanations. In the dumb money case, flows to arbitrage funds drive stock prices away from fundamental values. Mispricing corrects over time, generating reversals in stock returns and in the return to the quant strategy. By contrast, in the case of limits to arbitrage, mispricing arises from exogenous sources, and the flows to arbitrage strategies drive stock prices toward their fundamental values. The negative relation between flows and future quant returns in this case is due to an increase in cross-sectional market efficiency (and a corresponding reduction in return predictability), rather than to return reversal in underlying stocks. Thus, the two hypotheses differ in their empirical implications: Dumb money predicts a reversal in the relation between flows and future quant returns, and limits to arbitrage do not.

We conduct two tests (untabulated) to differentiate between the two explanations. First, we extend the holding period of stocks in the quant portfolio to see if we can detect any return reversal suggested by the dumb money explanation. Recall that the quant portfolio is rebalanced monthly, each month selecting stocks that score highest according to the value, profitability, momentum, reversal, and earnings factors. We increase the rebalancing period progressively up to 12 months, 1 month at a time. Portfolio trades still take place monthly, but each generation of stocks is now held for more than 1 month, resulting in two or more overlapping generations of stocks held in the portfolio at any given time. If the dumb money explanation is correct, returns to the quant strategy should reverse and vanish for longer holding periods. By contrast, under limits to arbitrage, quant returns should remain positive and significant for longer holding periods, capturing the slow stock price convergence toward fundamental value.

In our second test, we group all periods according to the sign of the abnormal flow variable (ABN_MF_FLOW6). Under the dumb money explanation, we expect to see a reversal in the performance of the quant strategy for the subsample corresponding to positive ABN_MF_FLOW6. That is, as the holding period increases from 1 to 12 months, the mean return of the quant strategy should drop to 0 or even turn negative. Contrary to the dumb money prediction, there is no evidence of return reversal at any horizon. To the contrary, returns are increasing for longer holding periods, suggesting that prices of stocks in the quant portfolio do not reverse but rather converge to fundamental values over a longer period.

We conclude that limits to arbitrage are the most likely explanation for the negative relation between fund flows and future quant returns. This conclusion is corroborated by the fact that this negative relation is also observed for hedge funds (Table 6). Given that hedge fund investors are generally sophisticated investors, they are less likely prone to the dumb money effect, so the fact that our results are robust to the use of hedge fund flows, rather than mutual fund flows, provides additional support for the limits-to-arbitrage explanation. We hasten to add that this conclusion is confined to the specific case of flows to arbitrage mutual funds studied in this article, and cannot be generalized to the entire universe of mutual funds. It is possible that a dumb money effect exists in aggregate mutual fund flows, without it being present in the small subset of mutual funds studied in this article, perhaps because funds that follow quant-based strategies do not automatically invest new funds into existing holdings, but rather rebalance their portfolio more frequently to invest in stocks that are recommended by the quant algorithm.

In fact, our results point to the possibility that at least some mutual fund flows meet the dumb money description of Frazzini and Lamont (2008). Of significant interest is the coefficient on MF_FLOW_X in Table 4. Recall that this variable measures the flows to mutual funds that are not deemed to be quant funds by the quant selection algorithm. Table 4 shows that the relation between MF_FLOW_X and future quant returns is positive, in contrast to the negative relation obtained with the quant flows. The positive relation suggests that flows to nonquant mutual funds could be invested in a manner that increases the mispricing of stocks that are held long by the quant strategy. Future research could explore this potentially important implication.

VII. Conclusion

We propose a rationale for why cross-sectional market efficiency, measured inversely by the profitability of a quant strategy based on capital market anomalies, varies over time. We document a negative relation between future returns to such a strategy and fund flows to this strategy. High flows to quant strategies speed up stock price convergence to efficient price levels, leading to lower cross-sectional predictability and lower returns to the quant strategy in the future, and vice versa.

These results provide a reasonable explanation for the persistence of cross-sectional return predictability, despite the increasing number of hedge funds that seek to trade based on the quant factors. Whenever stock prices are pushed away from equilibrium by exogenous forces, the presence of arbitrage capital is required to reestablish capital market efficiency. Absent such capital, predictability in the cross section of stock returns can persist. Conversely, if arbitrage capital were to become freely available at all times and without rationing, the cross-sectional predictability would disappear. However, so long as the availability of arbitrage capital is time varying, the stock market is likely to exhibit time-varying predictability of returns in the cross section.

Our work provides fertile ground for future research. For example, time variation in capital market anomalies within other countries remains 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. Anecdotal evidence (e.g., Jorion (2000)) from the Long-Term Capital Management case suggests that the fund's demise was caused by the managers' inability to raise the required arbitrage capital at a time when bond prices diverged the most from equilibrium values.

We also raise the question of how easy it is to actually earn abnormal returns by trading on cross-sectional predictability. Although 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 active funds do not outperform their benchmark despite the remarkable "paper" performance of quant strategies.

Finally, if the persistence of cross-sectional predictability is due to limits in the arbitrage capital that is needed to correct mispricing, the question remains open as to what caused this mispricing in the first place. Our results point to the possibility that mispricing might be caused, in part, by flows to nonquant mutual funds. Analyses of these and other issues are left for future research.

Appendix. Construction of Returns to the Quant Strategy

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 New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ). Quarterly accounting data and Standard Industrial Classification (SIC) codes are obtained from Standard & Poor's Investment Services' Compustat North America database (Compustat). To ensure realistic simulation of trading strategies, all accounting variables are based on quarterly data. We assume that accounting results are made public 2 months after the end of the reporting period. 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 Dec. 31, 2009 is less than $1 billion. For prior years, we deflate this cutoff with the CRSP value-weighted market return index. The base data set also excludes stocks with share prices lower than $5 or greater than $1,000.

A. Five Capital Market Anomalies

The quant strategy (QS) is a long–short hedge strategy designed to earn abnormal returns from 5 primary anomalies: price momentum, short-term reversal, profitability, relative value, and earnings. These 5 measures are derived from 10 underlying measures that are shown to predict equity market returns in the academic literature and are commonly used by industry practitioners (e.g., the Credit Suisse Alpha Score Card). Details of the 5 primary measures follow.

1. Price Momentum

Each month stocks are ranked into percentiles based on two measures of momentum: 6-month momentum and 6-month industry-adjusted momentum. Six-month momentum is calculated as the compounded return for the 6 months immediately preceding the portfolio-formation period. The 6-month industry-adjusted momentum is calculated as the compounded return for the 6 months immediately preceding the portfolio formation period minus the equal-weighted average return over the same period for all stocks in the same 2-digit SIC code. A momentum score for each stock is calculated as the equal-weighted average of the percentiles for these two underlying measures. One month is skipped between the measurement period and holding period for all momentum measures to minimize microstructure effects.

2. Short-Term Reversal

Following Jegadeesh (1990), each month stocks are ranked into percentiles based on two measures of short-term reversal: 1-month industry-adjusted price reversal and 5-day industry-adjusted price reversal. The 1-month reversal is measured as the rate of return during the 1-month period immediately preceding the holding period, minus the equal-weighted average return over the same period for all stocks in the same 2-digit SIC code. The 5-day industry-adjusted reversal is measured as the compound return for the 5 trading days immediately before the last trading day before the holding period (we skip 1 day to minimize microstructure effects) minus the equal-weighted average return over the same period for all stocks in the same 2-digit SIC code.

To compute the reversal score, we first invert the percentile ranks for the two measures above by subtracting that rank from 100. This is because we want scores to be interpreted the same way across all factors: higher score, higher abnormal return potential.

A reversal score is calculated for each stock as the equal-weighted average of the two (inverted) percentile ranks.

3. Relative Value

Each month stocks are ranked into percentiles based on two measures of relative value: cash-flow-to-value ratio and sales-to-value ratio (i.e., Ou and Penman (1989), Lakonishok, Shleifer, and Vishny (1994)). A value score is calculated as the equal-weighted average of the two percentile ranks corresponding to these two underlying measures.

The cash-flow-to-value ratio is computed as the average firm cash flow over the previous 12 months, divided by the market value of the firm's assets. This ratio is the inverse of the cash-flow multiple. A high cash-flow-to-value ratio (or low multiple) could have several causes: underpricing, high risk, or low cash-flow growth rate. Likewise, a low cash-flow-to-value ratio (high multiple) could indicate overpricing, low risk, or high growth rate. Active management takes the view that extreme values of the cash-flow-to-value ratio are more likely to indicate mispricing rather than differences in risk or growth rates, especially when these extreme values are observed among stocks within the same industry. To compute the cash-flow-to-value ratios, we estimate the cash flows 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. We then compute a 12-month cash-flow-to-value ratio as the average of the quarterly cash flows measured over the last 4 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 similar to the cash-flow-to-value ratio, with the exception that the average of the 4 quarterly net sales data is substituted for cash flows. A higher sales-to-value ratio is indicative of potential underpricing.

4. Profitability

Profitability is another attribute that correlates with the cross section of stock returns. Each month we sort stocks into percentiles based on 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 become a cross-sectional predictor of future returns (as suggested by, e.g., Rosenberg et al. (1985), Chan et al. (1991), and Piotroski (2000)). In untabulated results we verify that sorting stocks on ROA (and, respectively, on ROIC) leads to strong cross-sectional return predictability.

ROA is calculated as income for the most recent quarter divided by the book value of assets. ROIC 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. A profitability score is calculated as the equal-weighted average of the percentile ranks of the two underlying measures.

5. Earnings

Earnings have also been shown to predict stock returns in the cross section. There are two dimensions of earnings that predict returns. The first is earnings quality, measured inversely by accruals. Firms with higher accruals are more likely to capitalize an expense (rather than pass it through to the income statement) to boost short-term earnings. The literature documents a negative relation between accruals and subsequent stock returns (Sloan (1996)). The second dimension is the earnings surprise. Stock prices continue to move in the direction of the earnings surprise, even after the earnings have been announced (Bernard and Thomas (1989)).

To compute the earnings score, we rank stocks each month into percentiles based on the two earnings dimensions. Accruals are computed as in Sloan (1996) as the noncash change in current assets minus the change in current liabilities (excluding debt in current liabilities and income taxes payable) minus depreciation. We invert the percentile ranks for accruals by subtracting that rank from 100. For earnings surprises, we measure the cumulative abnormal returns (CARs) over the $[t-2, t+1]$ window surrounding the earnings announcement and compute a percentile rank for each stock by sorting the CARs in the cross section. The earnings score is the average of the percentile ranks of earnings quality (inverted) and earnings surprises.

B. Composite QS Factor Construction

To be included in the data set we require that a firm have valid (nonmissing) observations for each of the five 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 5th percentile are dropped from the data.

1. Security Selection

To implement QS we compute a monthly composite score for each stock by adding together the 5 factor scores of momentum, reversal, value, profitability, and earnings. Because each factor score ranges from 0 to 100, the composite score ranges from 0 to 500. A security whose composite score is high is expected to significantly appreciate in value, and vice versa. QS takes long positions on stocks with unusually high composite scores and short positions on stocks with unusually low composite scores, subject to industry matching, as described in the next subsection.

2. Industry Control

Long–short trading strategies such as QS 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. The main thesis in our article is that investors are reluctant to fund strategies with high volatility or large negative returns because of information asymmetry about managers. As a result, managers attempt to minimize intertemporal variance by matching stocks in the long and short portfolios according to risk characteristics. To ensure that QS is realistic and consistent with industry practice, we minimize the variance of the portfolio by pairing each stock in the long portfolio with a stock in the short portfolio selected from the same industry. This procedure is consistent with academic research showing that industry adjustment better explains cross-sectional variation in stock returns when compared to standard factor-based models (Johnson et al. (2009)).

We implement our industry pairing as follows. Each month, we sort firms into industry groups based on 2-digit SIC codes. Within each industry, we sort firms into 30 groups based on 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 stocks only in groups 30 and 1, as candidates for the long and short QS portfolios, respectively. We discard stocks in groups 2 to 29.

By pairing long and short stocks by industry, industrywide price movements in the long position will be mostly offset by similar movements in the short position, so the return of QS will primarily capture convergence toward fundamental values of mispriced securities. This type of industry matching also minimizes problems related to cross-sectional comparisons of accounting variables (e.g., book-to-market), which could vary widely across industries.

In some industries, the spread in composite scores between long stocks and short stocks is large. This implies a high level of cross-sectional inefficiencies (and higher alpha potential). In other industries, this spread is close to 0. A low spread is indicative of an industry where prices are relatively efficient, and the alpha potential is close to 0. To reduce noise in QS, we remove industries with low composite score spreads: those where the spread between the average long and short scores falls in the bottom 25% of all industry spreads. These are industries without significant 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.

3. Monthly Rebalancing

Each month, long and short portfolios are formed based on the composite scoring and industry pairing procedures outlined above. To ensure that QS captures the most recent information regarding cross-sectional mispricing, portfolios are rebalanced monthly using the latest factor scores and positions are being held for 1 month. The return to QS is computed as the equal-weighted average return of stocks in the long portfolio minus the equal-weighted average return of stocks in the short portfolio. Delisting returns are also included.

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