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Abstract

Have Capital Market Anomalies Attenuated in the Recent Era of High Liquidity and Trading Activity?

We examine whether the recent regime of increased liquidity and trading activity is associated with attenuation of prominent equity return anomalies due to increased arbitrage. We find that the majority of the anomalies have attenuated, and the average returns from a portfolio strategy based on prominent anomalies have approximately halved after decimalization. We provide evidence that hedge fund assets under management, short interest and aggregate share turnover have led to the decline in anomaly-based trading strategy profits in recent years. Overall, our work indicates that policies to stimulate liquidity and ameliorate trading costs improve capital market efficiency.

1 Introduction

Recent years have witnessed a sea change in trading technologies and the costs of transacting in capital markets. Chakravarty, Panchapagesan, and Wood (2005) and French (2008) document the significant decline in institutional commissions. Technology has facilitated algorithmic trading (Hendershott, Jones, and Menkveld, 2011), and hedge funds have proliferated. The improvements in trading technology and liquidity are dramatic and quite unprecedented.[1] Chordia, Roll and Subrahmanyam (CRS) (2011) show that these phenomena have been accompanied by an explosion in trading volume; the monthly, value-weighted average share turnover on the NYSE increased from 5% in 1993 to 35% in 2008, whereas it was virtually unchanged in the 1970s and 1980s. CRS also present evidence that it is institutional trading volume that accounts for this increase, and that this increased volume is associated with improvements in market quality.

In this paper, we investigate the economic notion that increased liquidity in recent years should have stimulated greater anomaly-based arbitrage and thus attenuated capital market anomalies. Our analysis is related to the recent strand of research that investigates whether increases in liquidity and trading activity are associated with greater efficiency.[2] We empirically explore how the Fama and MacBeth (1973) cross-sectional coefficient estimates and the decile-based hedge portfolio returns, have changed over time due to increased liquidity, and, in turn, increased arbitrage activity.

The literature on cross-sectional return predictors is vast. Ball and Brown (1968) document the post-earnings-announcement-drift (PEAD) where stocks with a high earnings

[1]In its more than 200 year history, the New York Stock Exchange (NYSE) has reduced the tick size only twice: from an eighth to a sixteenth in June 1997 and from a sixteenth to a penny in January 2001. Technological improvements have allowed the NYSE to accommodate a dramatic increase in trading volumes. Jones (2002) and Chordia, Roll, and Subrahmanyam (2001) show that standard measures of illiquidity such as bid-ask spreads have decreased substantially over time.

[2]See, for instance, Hendershott and Riordan (2011), Boehmer and Kelley (2009), Chordia, Roll, and Subrahmanyam (2008, 2011) and Roll, Schwartz, and Subrahmanyam (2007).

surprise continue to outperform stocks with a low earnings surprise. Jegadeesh (1990) and Lehmann (1990) document short-term reversals in stock returns. Fama and French (1992) document the size and the value effect. Returns are negatively related to firm size and positively to the book-to-market (BM) ratio. Jegadeesh and Titman (1993) uncover the momentum effect wherein buying past winners and selling past losers leads to substantial abnormal returns. Sloan (1996) investigates the accruals anomaly where stocks with greater non-cash components of earnings earn lower abnormal returns. Ang, Hodrick, Xing and Zhang (2006) document that stocks with high idiosyncratic volatility earn lower returns than stocks with low idiosyncratic volatility. Cooper, Gulen and Schill (2008) show that stocks with higher asset growth have lower returns than those with lower asset growth. Fama and French (2006) and Pontiff and Woodgate (2008) document the impact of profitability and new equity issuances, respectively.

Some of the above anomalies, such as earnings drift and momentum earn large paper profits, and have persisted out-of-sample long after their discovery (Bernard and Thomas, 1989, Rouwenhorst, 1999, Kothari, 2001), indicating that it is a challenge to attribute them to data mining. Further, it is difficult to come up with a risk-based story consistent with so many anomalies. This suggests that the anomalies may, at least in part, be arbitrageable. But, arbitrage, by its very nature, makes anomalies unstable, and subject to attenuation. This argument implies that the prevalence of anomalies may decline as secular increases in liquidity, trading activity, and technological trading innovations facilitate arbitrage. This is the motivation for our analysis. While other recent papers (e.g., Schwert, 2003, McLean and Pontiff, 2013) have also examined sets of anomalies, we contribute to the literature by examining how the profitability of the anomalies has been affected by liquidity-increasing events such as decimalization, as well as arbitrage proxies such as hedge fund assets under management, share turnover, and short interest.

In our sample, most anomalies are statistically significant for both NYSE/AMEX

(NYAM) and Nasdaq stocks. However, most of the hedge portfolio returns and the Fama-MacBeth coefficients attenuate towards zero over time. We conduct additional analysis to identify the reason behind the attenuation of the anomaly profits. Specifically, we try different identification schemes, including (i) the exogenous decrease in the tick size due to decimalization, (ii) the impact of hedge fund assets under management (AUM), (iii) the impact of the aggregate short interest, and (iv) aggregate share turnover. All of above variables are proxies for arbitrage activity.

The exogenous decrease in the tick size (and the bid-ask spread), due to decimalization, proxies for an exogenous decrease in trading costs that might have led to increased arbitrage activity. We find that the characteristic premiums (i.e., FM coefficients) of virtually all anomalies have attenuated from before to after decimalization, and the average returns as well as the Sharpe ratio from a comprehensive anomaly-based trading strategy have more than halved after the shift to decimal pricing. Further, the impact on returns of several anomalies, including momentum, accruals, idiosyncratic volatility, and earnings surprises, as well as the profits to a comprehensive portfolio trading strategy, has declined with an increase in hedge funds' AUM, short interest, and/or aggregate trading activity, indicating a link between arbitrage proxies and attenuation in anomalies. These results are consistent with the informal arguments of Schwert (2003) who, in reviewing anomalies documented during the 1970s and 1980s, suggests that increased arbitrage activity should limit the persistence of such anomalies.

A recent study by Fama and French (2008) explores various cross-sectional return predictors and finds that the most robust anomalies are those associated with momentum and accruals. Further, Korajczyk and Sadka (2004) explore the cross-sectional relation between momentum and trading costs. Our work adds to these studies by focusing on the *trend* in cross-sectional predictability. Specifically, we explore the notion that as trading technologies improve, anomaly-based predictability should diminish, both statistically and economically. Our results are broadly consistent with the economic notion implicit in Fama (1965, 1970) that technologies that reduce trading frictions and stimulate arbitrage facilitate market efficiency.[3]

A number of papers have also documented a decline in the anomaly profits in recent years. For instance, Mashruwalla, Rajgopal and Shevlin (2006) discuss how liquidity can attenuate anomalies (the accruals anomaly in particular). Bhushan (1994) points to trading activity as a facilitator and a proxy for arbitrage activity. Green, Hand and Soliman (2011) argue that the decline in profitability of the accrual based trading strategy is due to an increase in capital invested by hedge funds into exploiting it.[4] Our contribution is to simultaneously examine a number of the most prominent anomalies and to explicitly relate the decline in profitability to proxies for hedge fund activity.

The rest of the paper is organized as follows. Section 2 presents the list of anomalies we consider. Section 3 describes the data. Sections 4 consider portfolio and regression approaches, respectively. Section 5 considers possible rationales for attenuation, while Section 6 concludes.

2 The Anomalies

Our primary aim is to explore how a host of capital market anomalies have evolved in recent years, as stocks have become more liquid and more actively traded. The hypothesis is that as markets become more liquid and as trading costs decline, increased arbitrage activity would lead to a decline in the measured return premiums from these anomalies.

[3]Fama (1965) states that: "An 'efficient' market is defined as a market where there are large numbers of rational, profit-maximizers actively competing...in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value." It is reasonable to suppose that increases in liquidity and trading activity would increase the efficacy of rational, profit-maximizing arbitrageurs, and result in more efficient pricing.

[4]See also Khan (2008) and Richardson, Tuna, Wysocki (2010).

The firm characteristics included in our analyses, that capture well-known equity market anomalies, are the following:

1. SIZE: Measured as the natural logarithm of the market value of the firm's equity (Banz, 1981).

2. BM: Book equity for the fiscal year-end in a calendar year divided by market equity at the end of December of that year, as in Fama and French (1992).

3. TURN: The logarithm of the firm's share turnover, measured as the trading volume divided by the total number of shares outstanding (Datar, Naik, and Radcliffe, 1998).

4. R1: The lagged one month return (Jegadeesh, 1990).

5. R212: The cumulative return on the stock over the eleven months ending at the beginning of the previous month (Jegadeesh and Titman, 1993).

6. ILLIQ: The Amihud (2002) measure of illiquidity. This measure is the average daily price impact of order flow and is computed as the absolute price change per dollar of daily trading volume:

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} \times 10^6,$$

   where R_{itd} is the return for stock i, on day d of month t, $DVOL_{itd}$ is the dollar trading volume of stock i, on day d of month t, and D_{it} represents the number of trading days for stock i in month t.[5] Amihud and Mendelson (1986) have suggested that the level of liquidity should be priced in the cross-section.

[5]Though there are other measures of liquidity, the measure we use has the virtue of requiring only CRSP data for estimation, as opposed to voluminous transactions data that are only available since 1983. This measure also has been shown to have strong pricing effects in Amihud (2002).

7. ACC: Accounting accruals, as measured in Sloan (1996), defined as the change in non-cash current assets, less the change in current liabilities (exclusive of short-term debt and taxes payable), less depreciation expense, all divided by average total assets.

8. AG: Asset growth, as in Cooper, Gulen, and Schill (2008), computed as the year-on-year percentage change in total assets.

9. ISSUE: New issues, as in Pontiff and Woodgate (2008), measured as the change in shares outstanding from the eleven months ago.

10. IVOL: Idiosyncratic volatility, as in Ang, Hodrick, Xing, and Zhang (2006), computed as the standard deviation of the regression residual of the Fama and French (1993) three-factor model using daily data within a month.

11. PROFIT: Profitability, as in Fama and French (2006), calculated as earnings divided by book equity, where earnings is defined as income before extraordinary items.

12. SUE: Standardized unexpected earnings, computed as the most recently announced quarterly earnings less the earnings four quarters ago, standardized by its standard deviation estimated over the prior eight quarters. This is used to proxy for earnings surprises, in order to analyze post-earnings-announcement-drift (PEAD) as in Bernard and Thomas (1989, 1990), and Ball and Brown (1968).

We winsorize all the explanatory variables each month; values greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively.

3 Sample Description

The base sample includes common stocks listed on the NYSE/AMEX (NYAM) over the period January 1976 through December 2011. We also use Nasdaq stocks; however, this sample begins in 1983, since trading volume on Nasdaq, required for computation of turnover and the illiquidity measure, is not available prior to this date. The rationale for our sample period is as follows. Our basic argument is that a reduction in trading costs stimulates arbitrage and attenuates anomalies. In this regard, Jones (2002, Figure 4) shows that there was a steep decline in trading costs after the Big Bang (deregulation of brokerage commissions) in the mid-1970s, and trading costs were relatively stable prior to this period. Second, Chordia, Roll, and Subrahmanyam (2011) document the dramatic increase in trading volume in recent decades and suggest that prior to these decades, trading volumes were essentially unchanged. We argue that this considerable increase in trading volume and reduction in trading costs manifests itself starting largely from the mid-1970s, so that our sample period of 1976-2011 for NYAM and 1983-2011 for Nasdaq provides an ideal setting to test whether a regime of increased liquidity and trading activity, by allowing arbitrageurs to trade cheaply and to camouflage their trades more effectively, impacts cross-sectional predictability. Indeed, in the period 1950-1975 when aggregate share turnover for NYAM stocks (obtained from CRSP) was at about 2% per month we find no evidence of attenuation in the anomaly profits.

To be included in the monthly analysis, a stock has to satisfy the following criteria: (i) its return in the current month and over the past twelve months has to be available from CRSP, (ii) sufficient data has to be available to calculate market capitalization and turnover, and (iii) adequate data has to be available on Compustat to calculate the book-to-market ratio as of December of the previous year. In order to avoid extremely illiquid stocks, we eliminate stocks with month-end prices less than one dollar. The following securities are not included in the sample since their trading characteristics might differ from ordinary equities: ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks, and REITs.

Table 1 provides summary statistics (computed as the time series means of the monthly cross-sectional statistics) for the characteristics in the full sample. Nasdaq firms are smaller, less liquid, have higher idiosyncratic volatility, are less profitable, and, on net, issue more shares than NYAM firms. Nasdaq turnover is higher than that of NYAM stocks. However, Atkins and Dyl (1997) indicate that Nasdaq trading activity is overstated because of double counting of interdealer trading. For this reason, we separate Nasdaq and NYAM stocks in our analysis. We now turn to the results - first to an analysis of portfolios formed by sorting on the characteristics and then to the regression analysis.

4 The Anomalies

In this section, we first present the results of a portfolio analysis that considers the long-short return spread formed by sorting on the various anomalies, and subsequently the Fama-MacBeth coefficients.

4.1 Hedge Portfolio Returns

We examine the profitability of portfolios sorted on the lagged values of the different characteristics, as described in Section 2. We construct extreme decile portfolios that are long the high characteristic values and short the low characteristic values. In Panel A of Table 2, we provide the (equally-weighted) average raw returns of the long-short hedge portfolios along with the t-statistics for the null hypothesis that the average returns equal zero.

We see from Table 2 that for NYAM stocks, almost all the characteristic based portfolio returns are highly significant, both statistically and economically (the only exception is the profitability based portfolio). The hedge portfolio formed on the basis of the size (value) anomaly provides a monthly return of about 0.56% (1.0%) with a t-statistic of 2.10 (5.15). The reversal strategy provides a monthly return of 0.50% (t-statistic=2.37); the momentum strategy has a monthly return of 1.44% (t-statistic=4.61); a portfolio formed by sorting on turnover (illiquidity) has a monthly return of 0.49% (0.52%) with a t-statistic of 2.34 (2.17); accruals and asset growth provide highly significant monthly returns of 0.33% and 0.55% respectively; the new issues anomaly has a return of 0.93% per month; idiosyncratic volatility provides a monthly return of 0.64%; and PEAD provides a return of 0.74% per month. These results are not surprising given that we have chosen the anomalies based on what is known in the literature.

For Nasdaq stocks, size, reversals, and turnover are not significant at the 10% level, whereas all other anomalies are significant at this level, and the return magnitudes are quite comparable to those of NYAM stocks. Overall, we conclude that most of the anomalies are robust and obtain in NYAM as well as Nasdaq stocks.

4.2 Fama-MacBeth Coefficients

We now examine the anomalies via regression analysis. Our empirical methodology follows Brennan, Chordia, and Subrahmanyam (1998) (henceforth BCS). BCS test factor models by regressing individual firm risk-adjusted returns on firm-level attributes such as size, book-to-market, turnover and past returns. Under the null of exact pricing, such attributes should be statistically and economically insignificant in the cross-section. The use of individual stocks as test assets avoids the possibility that tests may be sensitive to the portfolio grouping procedure (Lo and MacKinlay, 1990).

We first obtain the risk-adjusted returns, $R_{jt}*$, as follows:

$$R_{jt}* = R_{jt} - R_{Ft} - \sum_{k=1}^{K} \beta_{jkt-1} F_{kt}, \tag{1}$$

where R_{Ft} is the risk-free rate, F_{kt} is the sum of the factor realization and the associated risk premium of the k'th factor at time t, β_{jkt-1} is the beta estimated for each stock by a first-pass time-series regression over the entire sample period.[6] The Fama and French (1993) factors, the UMD (momentum) factor of Carhart (1997), and the Pástor and Stambaugh (2003) liquidity factor are used to adjust for risk, and the one-year T-Bill rate is used as a proxy for R_{Ft}.[7] The risk-adjusted returns are then regressed on the equity characteristics:

$$R_{jt}* = c_{0t} + \sum_{m=1}^{M} c_{mt} Z_{mjt-k} + e_{jt}, \tag{2}$$

where Z_{mjt-k} is the k lagged value of the characteristic m for security j at time t, with M being the total number of characteristics. Following Brennan, Chordia, and Subrahmanyam (1998) we lag all characteristics by two months, i.e., k=2, except for R1, which by definition is lagged one month, and R212, which already is lagged two months. The procedure ensures unbiased estimates of the coefficients, c_{mt}, without the need to form portfolios, because the errors in estimation of the factor loadings are included in the dependent variable. The well known Fama and MacBeth (FM) (1973) estimators are the time-series averages of the regression coefficients, $\hat{c}_{mt}$. Since the cross-sectional standard deviation of the independent variable can change over time, we standardize the independent variables in the second stage cross-sectional regressions as follows. We subtract the monthly cross-sectional mean from each independent variable's observation and divide by

[6]See Fama and French (1992) and Avramov and Chordia (2006) who argue that using the entire time series to estimate the factor loadings gives the same results as using rolling regressions. Our analysis is also largely unaltered if we use rolling regressions to estimate the factor betas; results are available upon request.

[7]The results are not sensitive to whether risk factors are included; analyses without factors, and with only the three Fama and French factors, are available upon request.

the monthly cross-sectional standard deviation. Thus, all right-hand variables are scaled to have zero mean and unit standard deviation.

Panel B of Table 2 provides the estimates of the FM coefficients for the twelve anomalies. These coefficients represent the reward for exposure to the anomaly-based characteristics and we will often refer to these coefficients as "characteristic premiums." We again present results separately for NYAM and Nasdaq stocks. The results once again as expected given the anomalies literature. With the exception of turnover and profitability, all anomalies have significant characteristic premiums. As in the case of the long-short hedge portfolios, the coefficients are economically significant as well. For instance, a one standard deviation increase in firm size causes a 0.3% decrease in stock returns per month and a one standard deviation increase in the momentum variable causes a 0.2% increase in returns per month. The significance of most anomalies in the presence of others indicates that each anomaly exerts an independent and significant influence on returns. The characteristic premiums for Nasdaq stocks are generally of a magnitude comparable to that for NYAM stocks.

4.3 Exponential Trend in the Long-Short Portfolio Returns and Characteristic Premiums

In this subsection, we test the null that anomaly profits have not attenuated over time against the alternative of attenuation. Specifically, we fit the following exponential decay model,

$$Y_t = a \exp(bt + u),$$

where Y_t is one plus the hedge portfolio return or the characteristic premium in a given month, and t is a time index. We scale the time index to be between -1 and $+1$, so that the mean of the time variable is zero. The model is estimated in log-linear form, separately for NYAM and Nasdaq stocks, over the entire sample period.

Panel A of Table 3 provides the coefficients of the exponential time trend for the hedge portfolio returns (all coefficients are multiplied by 10). The coefficient estimate on time, $\hat{b}$, for the NYAM portfolio returns formed by sorting on the past one month return (reversal strategy) is 0.0124. An attenuation obtains when the trend is in the opposite direction of the baseline effect in Table 2. Since the return from buying (selling) stocks with low (high) values of the past month's return is -0.5% (from Table 2) per month, a positive trend coefficient is consistent with a decline in profits to a reversal strategy over time. The coefficient on cumulative returns over the past two to twelve months (momentum strategy) is -0.0142. Since the return to the momentum strategy is positive, a negative coefficient signifies a decline in profits over time. Similarly, the negative trend coefficient suggests a decline in profits to supplying liquidity.[8] The signs of the NYAM trend coefficient estimates suggest an attenuation in anomaly-based trading profits for ten of twelve anomalies.

Our alternative hypothesis is that anomalies should have *declined* in recent years due to increased liquidity and trading activity. Thus, in many parts of the paper we will present p-values of a one-tailed test of the null of no attenuation in the profitability of a specific anomaly-based strategy against the alternative of attenuation. These p-values for the NYAM sample appear in the third column of Table 3. We mostly use the 0.1 cutoff in the paper's exposition (so that the phrase "significant" in the context of attenuations, without further qualification, refers to the 10% level cutoff).

There is a significant decline in the profitability of eight of twelve of the anomalies for NYAM stocks. In the case of Nasdaq stocks, ten of twelve anomalies attenuate, with four (value, momentum, profitability, and PEAD) demonstrating significant attenuation. In Panel A of Table 3, we also provide the number of significant *accentuations* (at the 10%

[8] The significance in the NYAM time trend for illiquidity is consistent with Ben-Rephael, Kadan, and Wohl (2010).

level, i.e., the number of trend coefficients with a p-value exceeding 0.9). There is a strong asymmetry in significant attenuations and accentuations. While eight anomalies have significantly attenuated for NYAM stocks (four for Nasdaq stocks) only one anomaly has accentuated for NYAM stocks and no anomaly has significantly accentuated for Nasdaq stocks. The overall picture is quite consistent with attenuation in anomaly profits over time.

In the last row of Panel A of Table 3, we also present the result of fitting the exponential trend to the portfolio return obtained by equally weighting the twelve individual anomaly-based hedge portfolios (henceforth termed the "EW hedge portfolio"). The returns on this portfolio show a significant attenuation for both NYAM and Nasdaq stocks.

The economic significance of the trend can be assessed by computing the "half-life," i.e., the time taken for an anomaly to reduce to half its sample mean. We find that the time taken for momentum, accruals, SUE, and the EW hedge portfolio returns for NYAM to reduce to half their sizes are 7.4, 11.5, 13.4, and 12.8 years, respectively.[9]

Panel B of Table 3 tests whether there has been a decline in the FM coefficients. Again, we perform the analysis separately for NYAM and Nasdaq stocks. Eleven (nine) of twelve characteristic premiums attenuate for NYAM (Nasdaq) stocks. Six of the twelve NYAM characteristic premiums (those for size, monthly reversals, momentum, accruals, and profitability IVOL, and PEAD) exhibit a significant declining trend (five of these six cases attenuate with p-values of 0.05 or less). The half-lives for reversals, accruals, and SUE, are 5.4, 9.3, 10.2, and 6.7 years, respectively. For the Nasdaq stocks, we find that

[9]The half-life computations are conducted using the sample means of the natural log of one plus the hedge portfolio return, which, for small values, is close to the actual sample mean of the return, i.e., $\ln(1+Y) \approx Y$ for small Y. We then note that the overall sample period amounts to two time units (-1 to $+1$), which covers 432 months for NYAM, and 348 months for Nasdaq. As an illustrative calculation, the overall sample mean of the natural log of one plus the return for the NYAM EW hedge portfolio is 0.00644. Given the time slope of -0.0045, to reduce this number to half its value, i.e., to 0.00322 would take 0.712 time units, which amounts to 0.712*432/2 months or 12.8 years.

nine of twelve characteristic premiums attenuate albeit only four (momentum, reversals, turnover, and illiquidity) exhibit significant evidence of attenuation. Note that there are *no* cases of significant accentuation for any of the characteristic premiums.[10]

5 Sources of the Decline in Anomaly Profits

There are a number of possible reasons for attenuations in the anomalies:

1. Change in the risk-return trade-off. It is possible that the decline in the characteristic premiums has occurred due to some fundamental change in the dynamics of how risk is priced in the economy. While this argument cannot be fully ruled out, it has to explain the dramatic decline in the profitability of a large number of anomaly based trading strategies. We also note that many of the considered return predictors show a decline even after controlling for the Fama and French (1993) factors, by themselves and along with the Pástor and Stambaugh (2003) liquidity factor and a factor for momentum as in Carhart (1997). Further, a risk-based rationale for many of the predictors (especially variables such as accruals, momentum and one-month reversals) has been elusive.

2. Discovery of the anomalies due to numerous data mining exercises conducted by researchers. If this were the case, then a test of whether the anomaly survived its discovery would be informative.

3. Decline in trading costs and the improvement in liquidity over time. With a decrease in trading costs, it becomes possible for arbitrageurs to profitably trade on the anomalies and thus reduce the potential anomaly based profits.

[10]Since the anomalies could be correlated across each other, we orthogonalize each anomaly with respect to the others, and rerun the trend regressions. The inferences remain unchanged.

We now address the second and third rationales using the NYAM sample. Results for the Nasdaq sample are similar but, unsurprisingly, not as strong as the NYAM results presented below, and are available upon request.

5.1 The Impact of Discovery

In this section, we examine the characteristic premiums before and after discovery of the anomalies. The dates of discovery of the different anomalies are set as December of the year of publication.[11] This gives enough time for investors to set up potential trading strategies. The year of the publications along with the author names are as follows - size anomaly (Banz, 1981); book-to-market ratio (Fama and French, 1992); momentum (Jegadeesh and Titman, 1993); reversals (Jegadeesh, 1990); turnover (Datar, Naik and Radcliffe, 1998); accruals (Sloan, 1996); illiquidity (Amihud, 2002); new issues (Pontiff and Woodgate, 2008); idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006); profitability (Fama and French, 2006); and asset growth (Cooper, Gulen, and Schill, 2008). Since PEAD was first documented in Ball and Brown (1968), prior to the start of our sample period, this anomaly is not used in our pre- and post-discovery analysis.

Panel A of Table 4 presents the characteristic premiums before and after the discovery of the anomalies. The impact of firm size on the cross-section of returns has declined from before to after its discovery. The point estimate has declined from −0.690% from before its discovery to −0.182% (still statistically significant) after its discovery. The characteristic premium on reversals has declined but it is still statistically significant. The momentum premium has declined to insignificance. On the other hand, the characteristic premiums and their statistical significance for BM and idiosyncratic volatility have not changed at all suggesting that their discovery has not led to a decline in prof-

[11] Taking the date of publication to be the beginning of the year of publication does not result in any changes in the results.

itability. The characteristic premiums for profitability and new issues have increased and are statistically significant after their discovery. The point estimates for asset growth and new issues have also increased after their discovery but are statistically insignificant after their discovery, possibly due to the lack of data after the discovery. The signs of the coefficients suggest post-discovery attenuation in seven of eleven cases (not statistically different from chance), and three of these cases are significant.

Overall, the results are mixed. The characteristic premiums for firm size, reversals, and momentum, have declined significantly from before to after their discovery. However, the premiums for BM, idiosyncratic volatility, and new issues have not declined after their discovery, suggesting that data mining is not a likely rationale for the anomalies. Later, we will provide additional results that discriminate between discovery and arbitrage activity. McLean and Pontiff (2013) also investigate whether academic research attenuates anomalies. Our results are consistent with theirs as they attribute part of the post-publication decay to price pressure from "aware investors." Thus, McLean and Pontiff also suggest a role for arbitrageurs.

5.2 Subsample Analysis

We now examine the possibility that increased turnover and liquidity could have facilitated the attenuation of anomalies via increased arbitrage. In order to examine anomalies in the regime of sharply increased trading activity post-1993 (Chordia, Roll, and Subrahmanyam, 2011), we divide the sample into two equal sub-periods: 1976-1993 and 1994-2011. The FM coefficients appear in Panel B of Table 4. Size, reversals, momentum, idiosyncratic volatility and PEAD, all have significantly higher characteristic premiums in the first sub-period as compared to the second, suggesting that these premiums have indeed declined over time. The decline in the characteristic premiums of momentum and PEAD is particularly relevant because Fama (1998) classifies these as the two most prominent and robust anomalies. In economic terms, a one standard deviation increase in R212 results in an increase in monthly returns of 0.34% (0.09%) in the first (second) sub-period. Similarly, a one standard deviation increase in SUE results in an increase in monthly returns of 0.14% (0.01%). Moreover, the above monthly returns to momentum and PEAD are statistically insignificant in the second sub-period.

The (absolute) estimates of the characteristic premiums are lower in the second sub-period in all cases with just three exceptions (out of twelve), which are the asset growth anomaly, the new issues anomaly (both of which seem to provide higher returns in the second sub-period but these returns are not statistically significantly different from those in the first sub-period), and illiquidity. We observe that while nine of twelve anomalies attenuate, the attenuation in anomalies is significant in five of 12 cases. The penultimate row of Panel B compares the return of the EW hedge portfolio across the first and second sub-periods. We find that the return decreases from an average of 0.85% per month in the first half of the sample to 0.46% per month in the second half, and this decrease is strongly significant. The last row provides the Sharpe ratio for the EW hedge portfolio. The ratio declines from 0.74 in the first subperiod to 0.31 in the second subperiod (i.e., more than halves in the later period), and this decline is strongly significant.[12] Thus, both the mean return and the reward-to-risk ratio decline, economically and statistically, in the second subperiod relative to the first.

5.3 Testing for Arbitrage

To directly test for arbitrage we try different identification schemes: (i) exogenous decrease in the tick size due to decimalization, (ii) assets under management of hedge funds, (iii) short interest and (iv) share turnover. These variables are proxies for arbitrage ac-

[12]In Panel B (and in Panel C to follow), we use the Jobson and Korkie (1981) approach to test for attenuation in the Sharpe ratio.

tivity.

5.3.1 Decimalization

We first use decimalization to proxy for an exogenous decrease in trading costs that might have led to increased arbitrage activity. We do this by stratifying the sample by the month of decimalization (January 2001)[13] and present the FM coefficients for the pre- and post-decimalization period, together with the attenuation p-values. The results in Panel C of Table 4 show that the characteristic premiums have declined towards zero for all the anomalies, and five of twelve anomalies show a statistically significant attenuation. After decimalization, except for the premium on size, none of the characteristic premiums are statistically significant at the 5% level. Overall, while the paucity of significant attenuations (only five of twelve) can be attributed to fewer observations in the post-decimal period, attenuation in the point estimate of all of the anomalies is unlikely to arise from chance alone.

Note that since the Fama-MacBeth coefficients are standardized, the coefficients represent the impact of a one standard deviation move in the independent variable and hence also capture economic significance. In Panel B, the economic significance declines in the second sub-period (relative to the first) for eight out of the twelve anomalies that we consider. Further, in Panel C, all anomalies are less economically significant in the post-decimalization period relative to the pre-decimalization period. The decline in economic significance is substantial: for instance, the impact of monthly reversals declines by 43%, that of illiquidity by 39%, and that of SUE by 55%.

We now discriminate between discovery versus trading costs as the potential cause of

[13]The post decimalizaton period coincides with the post Regulation Fair Disclosure period. Eleswarapu, Thompson and Venkataraman (2004) find that trading cost measures such as effective spreads and price impact have declined after the adoption of Reg FD on October 23, 2000. Thus, both Reg FD and decimalization have led to a decrease in trading costs after January 2001.

the decline in the anomaly profits. The impact of firm size, reversals, book/market, and idiosyncratic volatility continues to be significant (at the 10% level) after their discovery (Panel A of Table 4) but only size remains significant after decimalization. Further, in the other cases, the point estimates of the characteristic premiums are statistically lower in absolute terms after decimalization. This is consistent with the notion that while discovery and increased arbitrage are not mutually exclusive, it is the reduction in trading costs as proxied by decimalization that is associated with a reduction in the characteristic premiums that we document in our paper.

In the second-to-last row of Panel C, we also compare the return on the EW hedge portfolio pre- and post-decimalization. We find that the return on this portfolio reduces considerably from an average of 0.77% per month before decimalization to 0.40% per month after decimalization (both numbers remain significant). Further, this decrease of 0.37% in absolute terms and 48% in proportional terms is economically material and also is statistically significant with a p-value of 0.004.[14]

In comparison, the value weighted proportional quoted spread has declined from 0.50% to 0.08% accompanied by a decline in the average quoted depth (average number of shares available to trade at the bid and the ask) from 10,000 shares to 2,800 shares. While there has been a significant decline in the spread, the number of shares available for trade after decimalization has also significantly declined. Thus, any sizeable trade is likely to have a noticeable price impact. The last row provides the Sharpe ratios for the EW hedge portfolio before and after decimalization. The ratio declines from 0.66 in the pre-decimal period to 0.24 in the post-decimal period, i.e., by about two-thirds. This

[14]Our post-decimalization results on attenuation in anomaly profits complement those in Israel and Moskowitz (2012) as well as Frazzini, Israel, and Moskowitz (2012); however, our study is not directly comparable to these papers, because they focus primarily on size, value, and momentum and do not explicitly consider the post-decimalization period, whereas we consider twelve anomalies, and also focus on dramatic declines in trading costs and increases in trading activity that have occurred in the more recent years.

decrease also is strongly significant.

5.3.2 Hedge Fund Assets and Short Interest

Next, we consider hedge fund assets under management (AUM), scaled by the previous month's value-weighted market capitalization for NYAM stocks.[15] Note that we do not have data on the actual trades of hedge funds, which would have been a better measure of arbitrage activity. The idea is to test whether the growth of the hedge fund industry has led to a decline in the anomaly-based profits. Since shorting is an important component of arbitrage, we also use the value-weighted monthly short interest for our sample period as a fraction of the previous month's outstanding shares to proxy for arbitrage activity. The sample period for hedge funds AUM is from February 1977 through December of 2011 and for short interest it extends from January of 1976 through December of 2011.

We model each characteristic premium and the return on the EW hedge portfolio as an ARIMA process with a transfer function that uses hedge fund AUM and short interest, in turn, as input series. The transfer function relating an output series Z_t to an input series X_t takes the general form:

$$Z_t = \alpha + \frac{\omega(B)}{\delta(B)} X_t + \frac{\gamma(B)}{\kappa(B)} u_t, \tag{3}$$

where u_t is white noise, B is the backshift operator, and $\omega(B)$, $\delta(B)$, $\gamma(B)$, and $\kappa(B)$, are arbitrary polynomials (referred to as numerator and denominator polynomials) in B. One issue is that in our sample, both AUM and short interest have trended upward significantly. The positive trend in these variables, and the negative trend in the anomalies (Table 3) is consistent with the notion that arbitrage has attenuated anomalies. But because the series all show a trend, attributing causation is difficult. Thus, we conduct

[15] We thank Matti Suominen and LIPPER-TASS for data on hedge fund AUM. The sample includes all hedge funds that report their returns in U.S. dollars and have a minimum of 36 monthly return observations over our sample period.

a time-series analysis with the detrended (stationary) series to ascertain time-series relationships between the series. Prior to their use in our analysis, we detrend all of the series using linear and quadratic terms. Returns for the EW hedge portfolio are first orthgonalized with respect to the three Fama and French (1993) factors, the momentum factor as in Carhart (1997), and the Pástor and Stambaugh (2003) liquidity factor. Note that the characteristic premiums are already risk-adjusted. The resulting series provide no evidence of non-stationarity, as per the augmented Dickey-Fuller test, allowing us to conduct our time-series analysis.

We follow Liu (2006) in modeling the time series. We first determine the initial transfer function weights by a simple regression of Z_t on the contemporaneous and lagged values of the input series X_t. These weights exhibit a cutoff pattern; lags beyond ten are abruptly insignificant. This suggests modeling the decay polynomial $\delta(B)$ as unity. The univariate modeling of the residual series from the OLS regression suggests an ARMA(1,1) process for innovations to each of the series.[16] We select the polynomial $\delta(B)$ in (3) such that its highest power (denoted by T) is that of the longest lag that is significant in the simple regression, up to a maximum of ten lags. The order of the polynomial varies from four through 10. Thus, the final model estimated is

$$Z_t = \alpha + \sum_{k=0}^{T} \omega_k B^k X_t + \frac{1 - \gamma_1 B}{1 - \kappa_1 B} u_t. \tag{4}$$

All sample autocorrelations of the estimated u_t are insignificantly different from zero. We also examine the cross-correlations between the residuals and the input series and find that all of them are insignificantly different from zero. Panel A of Table 5 presents the cumulative coefficients (i.e., the ω_k's) for hedge fund AUM and short interest, as well as the p-values for the test that these coefficients are jointly significant. We infer attenuation or accentuation by the sign of the cumulative coefficients.

[16]We use the smallest canonical (SCAN) correlation method (Tsay and Tiao, 1985) to identify the ARMA order of each of the series.

We find that the characteristic premiums of all anomalies except for the book-to-market ratio decline significantly with an increase in hedge fund AUM, and all characteristic premiums except for those for the book-to-market ratio and asset growth decline significantly with an increase in short interest, suggesting that AUM in the hedge fund industry and shorting activity have indeed led to a decline in the profitability of the anomaly based trading strategies. As many as eleven (ten) of the twelve coefficients on hedge fund AUM (short interest) are of a sign that indicates that increases in hedge fund AUM (short interest) are associated with attenuation in the anomalies, and seven each are significant.

The last row of Table 5, Panel A provides results for the EW hedge portfolio. The EW hedge portfolio returns are negatively related to both arbitrage proxies. There is reliable evidence that the risk-adjusted returns to a comprehensive anomaly-based portfolio attenuate significantly with an increase in hedge fund AUM and short interest. As a robustness check, we also estimate a seemingly unrelated regression (SUR), by stacking the time-series of the 12 characteristic premiums and regressing the stacked panel on one lag of the arbitrage proxies. This estimation allows for cross-correlations in the error terms across the anomalies. The results continue to support attenuation, and are available upon request.

In economic terms, a one standard deviation change in hedge fund AUM cumulatively changes the characteristic premium of reversals by 0.143% per month. Based on the characteristic premium for R1 of 0.327% documented in Table 3, a one standard deviation increase in AUM results in a reduction of 43% in the (absolute) characteristic premium for R1. Similar computations show a decline of 77% for accruals, and a 45% attenuation in the size effect. Using analogous arguments, a one standard deviation increase in the aggregate value-weighted short interest more than halves the premium for accruals, momentum, and SUE. The equally-weighted hedge portfolio return attenuates by 37%

and 43%, respectively, in response to a one standard deviation increase in AUM and short interest, respectively.

The ARIMA/transfer function analysis treats the characteristic premiums as endogenous variables, and hedge fund AUM/short interest as exogenous variables. However, bidirectional causality between hedge fund AUM/short interest and the characteristic premiums is a possibility since large anomaly returns might attract more hedge fund assets or short interest. In order to attribute causation econometrically, while allowing for this endogeneity, we now present results from a multivariate vector autoregression (VAR) of the characteristic premiums, and the two arbitrage proxies, hedge fund AUM and short interest. We also present results when we replace the characteristic premiums with the equally weighted hedge portfolio return. Thus, consider the system

$$\begin{aligned} Z_t &= \sum_{j=1}^{K} a_{1j} X_{t-j} + \sum_{j=1}^{K} b_{1j} Z_{t-j} + u_t, \\ X_t &= \sum_{j=1}^{K} a_{2j} X_{t-j} + \sum_{j=1}^{K} b_{2j} Z_{t-j} + v_t, \end{aligned}$$

where Y is a time series that represents either a characteristic premium or the EW hedge portfolio return, whereas the vector X represents the arbitrage proxies. The lag length for the VARs is determined by the Akaike information criterion, the Schwarz information criterion, the Final Prediction error, and the Hannan-Quinn information criterion. We determine the lag length for each of the anomalies as follows. If three of the four criteria agree on a lag length, we choose that length. If not, we choose the maximum lag length indicated across all of the criteria. The range of the lag length is four to 10. For the null hypothesis that a variable i does not Granger-cause a variable j, we test whether the lagged coefficients of i are jointly zero when j is the dependent variable in the multivariate VAR. All variables are linearly and quadratically detrended prior to the VAR; further, we also dummy out the date of decimalization, and for the EW hedge portfolio return series, include the five factors of Section 4.2 as exogenous variables.[17] The resulting series all indicate stationarity based on the augmented Dickey-Fuller tests.

Panel B of Table 5 documents the p-values associated with the Granger causality tests. The results show that hedge fund AUM Granger-causes the characteristic premiums for size, reversals, momentum, accruals, asset growth, idiosyncratic volatility, and the post-earnings-announcement-drift, and also Granger causes the EW hedge portfolio return. We also report the cumulative coefficients of the VAR, which indicate attenuation in nine of twelve of anomalies. The cumulative sign is negative for the EW hedge portfolio return, and the p-value is less than 0.001, which also points to a reduction in the aggregate anomaly profits upon an increase in hedge fund AUM. Similar results obtain for short interest which Granger-causes the characteristic premiums for size, reversals, momentum, turnover idiosyncratic volatility and the post-earnings-announcement-drift as well as the EW hedge portfolio returns. The last column shows the adjusted R^2s which range from 0.2% to 14%. The best model fit obtains for the characteristic premiums for momentun and asset growth which have R^2s of 12.8% each and for the EW hedge portfolio which has an R^2 of 14%.

Results for reverse causality, i.e., whether the relevant anomaly Granger-causes hedge fund AUM or short interest are omitted for brevity. While the arbitrage proxies Granger-cause each other, the characteristic premiums or the EW hedge portfolio returns largely do not Granger-cause the proxies. In the last column, we test for the joint significance of the lagged coefficients on hedge fund AUM and short interest. The coefficients are jointly significant in eight of twelve cases for the characteristic premiums, and also for the EW hedge portfolio, with a p value of less than 0.001. These results confirm the single

[17]Whether these exogenous variables are included makes virtually no difference to the central results. Note that the lag length can differ for the VAR relative to the ARIMA model because the ARIMA approach is a single equation analysis with the characteristic premium as the explanatory variable, whereas the VAR captures bidirectional causality.

equation ARIMA analysis and accord with the notion that higher arbitrage activity attenuates capital market anomalies.

5.3.3 Trading Volume

We now examine the role of the value weighted market share turnover. Chordia, Roll and Subrahmanyam (2011) have argued that recent years have seen a remarkable increase in trading activity due to reductions in trading-related frictions and much of the increase in trading volume obtains due to trading by institutional investors. Datar, Naik, and Radcliffe (1998) argue that this variable is an important direct measure of liquidity, because the cost of turning around a position is lower when the stock is more actively traded. The sample period for share turnover is from January 1976 through December 2011.

Panel A of Table 6 presents the cumulative coefficients of share turnover, where the transfer function is selected as per the procedure in Section 5.3.2. Higher share turnover is associated with attenuation in the anomalies in each of twelve cases for the characteristic premiums. The last row of Panel A of Table 6 shows that the equally weighted hedge portfolio return also attenuates significantly with increasing turnover. Thus, increased turnover is reliably associated with attenuation in the anomalies. Considering economic significance, a one-standard-deviation move in share turnover attenuates reversals by 50%, accruals by 57%, the size effect by 56%, and the equally-weighted hedge portfolio return by 39%.

A potential issue is whether turnover simply proxies for hedge fund AUM and short interest. To address this issue, in Panel B of Table 6, we add the value-weighted turnover to the multivariate VARs in Panel B of Table 5. The cumulative signs of the coefficients indicate that share turnover, AUM, and short interest are associated with attenuation in nine, eight, and nine of twelve characteristic premiums respectively. Furthermore, increases in AUM, turnover, and short-interest are all associated with reductions in returns on the EW hedge portfolio. Thus, an increase in trading activity is associated with a decrease in the anomaly-based return even after accounting for the impact of AUM and short interest. The last column of Panel B conducts a test of whether the lagged coefficients on the three arbitrage proxies are jointly significant. The coefficients are indeed significant in eleven of twelve cases, and ten of them are significant. The lagged coefficients in the case of the EW hedge portfolio are also significant with a p-value of less than 0.001. The last column shows the adjusted R^2s which range from 0.5% to 18.3%. Once again the highest R^2 is for the characteristic premium for momentum at 17.8% and for the EW hedge portfolio at 18.3%.

We have also included macroeconomic variables such as inflation, the term spread (the yield differential between Treasury bonds with more than ten years to maturity and Treasury Bills that mature in three months, and the credit spreads (the yield differential between bonds rated Baa and Aaa by Moody's) as exogenous variables in the VAR, to ascertain whether macroeconomic cycles might explain variation in anomaly-based returns. These variables are consistently insignificant in explaining the anomalies, suggesting that the decline in the anomaly based trading strategy profits are more pervasive than the business cycle. Overall, the results provide evidence that the proxies for arbitrage trading - decimalization, short interest, hedge fund assets under management, and aggregate trading activity, are all linked to a decrease in the strength of capital market anomalies.

6 Summary and Concluding Remarks

We study several equity market anomalies over more than three decades, and find that the regime of increased liquidity and trading activity have resulted in a decrease in the economic and statistical significance of these anomalies.

In order to establish a link between increased arbitrage activity and the decline in the profitability of the anomaly based trading strategies we examine (i) the impact of the decline in the tick size due to decimalization and (ii) the impact of hedge fund assets under management, short interest, and trading activity on the anomaly based predictability. The exogenous decrease in the tick size has resulted in improvements in liquidity and a decline in trading costs. We find that the characteristic premiums have declined towards zero for several anomalies in the post-decimal period, and the profits to a comprehensive anomaly-based portfolio have declined by about half in the post-decimal period. Moreover, the impact of many anomalies such as size, reversals, momentum, and PEAD, as well as the return to a composite portfolio have declined with an increase in hedge fund assets, short interest, and aggregate share turnover, suggesting that arbitrage activity has indeed led to a decline in the profitability of the anomaly based trading strategies.

These results are relevant because they indicate that it may be challenging to attain consistent profits from well-documented anomalies in the future. Note, however, that while anomaly profits based on a composite NYAM portfolio decline significantly in the recent high-liquidity era, they remain statistically significant. Looking to the future, these profits may not disappear completely because of limits to arbitrage (Shleifer and Vishny, 1997) or imperfect competition amongst arbitrageurs (Kumar and Seppi, 1994) that preserves some rents.

Our analysis suggests that it might be fruitful to explore the effect of mechanisms and policies that remove trading frictions and improve liquidity in markets. The results suggest that cross-sectional return predictability would diminish to a greater extent in countries that have experienced greater enhancements in trading technologies and larger increases in trading activity and liquidity. This hypothesis awaits rigorous testing in an international context.

References

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

Amihud, Y., and H. Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Atkins, A., and E. Dyl, 1997, Market structure and reported trading volume: Nasdaq versus the NYSE, *Journal of Financial Research* 20, 291-304.

Avramov, D., T. Chordia, and A. Goyal, 2006, Liquidity and autocorrelations in individual stock returns, *Journal of Finance* 61, 2365-2394.

Baker, M., and J. Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271-299.

Ball, R., and P. Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-178.

Ball, C., and T. Chordia, 2001, True spreads and equilibrium prices, *Journal of Finance* 56, 1801-1836.

Banz, R., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Ben-Rephael, A., O. Kadan, and A. Wohl, 2010, The diminishing liquidity premium, working paper, Tel Aviv University.

Bernard, V., and J. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or characteristic premium?, *Journal of Accounting Research* 27, 1-36.

Bernard, V., and J. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305-340.

Bessembinder, H., 2003, Trade execution costs and market quality after decimalization, *Journal of Financial and Quantitative Analysis* 38, 747-777.

Bhushan, R., 1994, An informational efficiency perspective on the post-earnings announcement drift, *Journal of Accounting and Economics* 18, 45-66.

Boehmer, E., and E. Kelley, 2009, Institutional investors and the informational efficiency of stock prices, *Review of Financial Studies* 22, 3563-3594.

Brennan, M., T. Chordia, and A. Subrahmanyam, 1998, Alternative factor specifications, security characteristics and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345-373.

Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chakravarty, S., V. Panchapagesan, and R. Wood, 2005, Did decimalization hurt institutional investors?, *Journal of Financial Markets* 8, 400-420.

Chordia, T., A. Goyal, G. Sadka, R. Sadka and L. Shivakumar, 2009, Liquidity and the post-earnings-announcement-drift, *Financial Analysts Journal* 65, 18-32.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, Market liquidity and trading activity, *Journal of Finance* 56, 2, 501-530.

Chordia, T., R. Roll, and A. Subrahmanyam, 2008, Liquidity and market efficiency, *Journal of Financial Economics* 87, 249-268.

Chordia, T., R. Roll, and A. Subrahmanyam, 2011, Recent trends in trading activity and market quality, *Journal of Financial Economics* 101, 243-263.

Chordia, T., A. Sarkar, and A. Subrahmanyam, 2011, Liquidity dynamics and cross-auto-correlations, *Journal of Financial and Quantitative Analysis* 46, 709-736.

Collins, D., and P. Hribar, 2000, Earnings-based and accrual-based market anomalies: one effect or two?, *Journal of Accounting and Economics* 29, 101-123.

Cooper, M., H. Gulen, and M. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609-1651.

Daniel, K., R. Jagannathan, and S. Kim, 2012, Tail risk in momentum strategy returns, working paper, Columbia University.

Datar, V., N. Naik, and R. Radcliffe, 1998, Liquidity and stock returns: An alternative test, *Journal of Financial Markets* 1, 203-219.

Domowitz, I., J. Glen, and A. Madhavan, 2001, Liquidity, volatility and equity trading costs across countries, *International Finance* 4, 221-255.

Eleswarapu, V., R. Thompson, and K. Venkataraman, 2004, The Impact of Regulation Fair Disclosure: Trading costs and Information asymmetry, /it Journal of Financial and Quantitative Analysis 39, 209-225.

Fama, E., 1965, Random walks in stock market prices, *Financial Analysts Journal* September-October, 55-69.

Fama, E., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25, 383-417.

Fama, E., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics*, 49, 283-306.

Fama, E., and K. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, E., and K. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E., and K. French, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491-518.

Fama, E., and K. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653-1678.

Fama, E., and J. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Francis, J., R. LaFond, P. Olsson, and K. Schipper, 2005, The market pricing of accruals quality, *Journal of Accounting and Economics* 39, 295-327.

Frazzini, A., R. Israel, and T. Moskowitz, 2012, Trading costs of asset pricing anomalies, working paper, University of Chicago.

French, K., 2008, The cost of active investing, *Journal of Finance* 63, 1537-1573.

Gao, X., and J. Ritter, 2010, The marketing of seasoned equity offerings, *Journal of Financial Economics* 97, 33-52.

Green, J., J. Hand, and M. Soliman, 2011, Going, going gone? The apparent demise of the accruals anomaly, *Management Science* 57, 797-816.

Hendershott, T., C. Jones, and A. Menkveld, 2011, Does algorithmic trading improve liquidity?, *Journal of Finance* 66, 1-33.

Hendershott, T., and R. Riordan, 2011, High frequency trading and price discovery, working paper, University of California at Berkeley.

Israel, R., and T. Moskowitz, 2012, The role of shorting, firm size and time on market anomalies, forthcoming, *Journal of Financial Economics.*

Jegadeesh, N., 1990, Evidence of predictable behavior in security returns, *Journal of Finance*

45, 881-898.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-92.

Jobson, J., and B. Korkie, 1981, Performance hypothesis testing with the Sharpe and Treynor measures, *Journal of Finance* 36, 889-908.

Jones, C., 2002, A century of stock market liquidity and trading costs, working paper, Columbia University, and available at http://www.ssrn.com/abstract_id=313681.

Jylhä, P., and M. Suominen, 2011, Speculation capital and currency carry trades, *Journal of Financial Economics* 99, 60-75.

Khan, M., 2008, Are accruals mispriced? Evidence from tests of an intertemporal capital asset pricing model, *Journal of Accounting and Economics* 45, Pages 55-77.

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

Kothari, S., 2001, Capital market research in accounting, *Journal of Accounting and Economics* 31, 105-231.

Kumar, P., and D. Seppi, 1994, Information and index arbitrage, *Journal of Business* 67, 481-509.

Lehmann, B., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Lev, B., and J. Ohlson 1982, Market-based empirical research in accounting: A review, interpretation, and extension, *Journal of Accounting Research* 20 [*Supplement: Studies on Current Research Methodologies in Accounting: A Critical Evaluation*], 249-322.

Lewellen, J., 2002, Momentum and autocorrelation in stock returns, *Review of Financial*

Studies, 15, 533-563.

Liu, L.-M., 2006, *Time series analysis and forecasting*, Scientific Computing Associates, Chicago, IL.

Lo, A., and C. MacKinlay, 1990, Data-snooping biases in tests of financial asset pricing models, *Review of Financial Studies* 3, 431-468.

Mashruwalla, C., S. Rajgopal, and T. Shevlin, 2006, Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs, *Journal of Accounting and Economics* 42 [Conference Issue on *Implications of Changing Financial Reporting Standards*], 3-33.

McLean, D., and J. Pontiff, 2011, Does academic research destroy stock return predictability?, working paper, Boston College.

Novy-Marx, R., 2012, Is momentum really momentum?, *Journal of Financial Economics* 103, 429-453.

Pontiff, J., and A. Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921-945.

Richardson, S., I. Tuna, and P. Wysocki, 2010, Accounting anomalies and the fundamental analysis: A review of recent research advances, *Journal of Accounting and Economics* 50, 410-454.

Rouwenhorst, K., 1999, Local return factors and turnover in emerging stock markets, *Journal of Finance* 54, 1439-1464.

Schwert, W., 2003. Anomalies and market efficiency, in Constantinides, G., Harris, M., and Stulz, R. (eds.), *Handbook of the Economics of Finance*, edition 1, volume 1, chapter 15, pp. 939-974, Elsevier, Netherlands.

Shleifer, A., and R. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Sloan, R., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting Review* 71, 289-315.

Stambaugh, R., J. Yu, and Y. Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Tsay, R., and G. Tiao, 1985, Use of canonical analysis in time series model identification, *Biometrika* 72, 299-315.