Trends in the Cross-Section of Expected Stock Returns

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Abstract

We examine whether the recent regime of increased liquidity and trading volume is associated with attenuation of equity return anomalies. The profitabilities of several anomaly-based trading strategies have attenuated significantly over time, particularly in liquid NYSE/AMEX stocks, and virtually none have significantly accentuated. The profits from a composite strategy based on all of the anomalies show a strong downward trend. Hedge fund assets under management, short interest, and the post-decimalization decline in trading costs, are associated with declines in anomaly-based trading strategy profits in recent years, indicating that increased arbitrage activity may have led to this decline in anomaly-based trading strategy profits.

Recent years have witnessed a sea change in trading technologies and the costs of transacting in financial markets. For instance, Chakravarty, Panchapagesan, and Wood (2005) and French (2008) show that institutional commissions have declined over time. Chordia, Roll, and Subrahmanyam (2001) show that standard measures of illiquidity such as bid-ask spreads have also decreased substantially over time. Further, technology has facilitated algorithmic trading by institutions (Hendershott, Jones, and Menkveld, 2011), and hedge funds have proliferated. The improvements in trading technology and decreases in trading costs 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 value-weighted average share turnover on the NYSE jumped from 5% in the 1980s 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 examine whether "anomalies" in the cross-section of equity returns have attenuated in recent years. The economic notion we investigate is that reduced trading costs should have stimulated greater anomalies-based arbitrage and reduced cross-sectional return predictability. Thus, our analysis continues work in the recent strand of literature that investigates whether liquidity and trading activity facilitate efficiency.[2]

[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.

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

The literature on cross-sectional return predictors is vast. Thus, Ball and Brown (1968) document the post-earnings-announcement-drift (PEAD) where stocks with a high earnings 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) find that firm size and the book-to-market (BM) ratio strongly predict future returns. Returns are negatively related to size and positively to BM. Jegadeesh and Titman (1993) uncover a 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 like earnings drift and momentum earn large paper profits, and have persisted out-of-sample long after their discovery (Bernard and Thomas, 1989, Rouwenhorst, 1999), 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. If they are, then their profitability may decline as liquidity increases and facilitates arbitrage, and this is the motivation for our analysis.

We find that most anomalies are statistically significant in our full sample, for both NYSE/AMEX (NYAM) and Nasdaq stocks, both via portfolio and regression analyses. When we regress returns to extreme-decile hedge portfolios on a time trend, we find that almost all of the trend coefficients point towards attenuation. For NYAM stocks, the attenuation is significant with a *p*-value below 0.1 for nine of twelve anomalies. For Nasdaq, the corresponding number is only four of twelve. A composite portfolio strategy based on all of the anomalies also points to the notion that the profitability of anomalies has decreased over time, with a *p*-value of less than 0.01. Analysis of the Fama-MacBeth (1973) (FM) regression coefficients indicates that these also attenuate in virtually all cases, and several anomalies show significant evidence of attenuation for NYAM stocks; fewer for Nasdaq stocks, and virtually no anomalies significantly accentuate. For the relatively liquid NYAM stocks, the FM coefficients attenuate towards zero for nine of twelve anomalies (eight of twelve with a *p*-value of less than 0.1). For illiquid NYAM stocks, five of twelve anomalies attenuate significantly. This evidence that cross-sectional predictability has declined over time for stocks that have experienced the most increase in liquidity (the liquid NYAM stocks)[3] is suggestive of the impact of increased arbitrage activity.

We conduct additional analysis in order to address why the profitability from anomalies has changed over time. 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 and (iii) the impact of short interest. All of above variables are proxies for arbitrage activity.

[3] See Chordia, Sarkar, and Subrahmanyam (2011).

First, we note that 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 (absolute) characteristic premiums (i.e., coefficients from Fama and MacBeth, 1973, regressions) of virtually all anomalies have attenuated from before to after decimalization, and the profits from a composite trading strategy have more than halved after the shift to decimal pricing. We also use hedge funds' assets under management (AUM) as a fraction of market capitalization and aggregate short interest as a fraction of the previous month's outstanding shares to proxy for arbitrage activity. We find that the impacts of firm size, reversals, momentum, accruals, idiosyncratic volatility, and SUE on returns, as well as the profits to a composite trading strategy, have declined with an increase in AUM and short interest, suggesting that arbitrage activity has indeed led to a decline in the profitability of the anomaly based trading strategies.

A recent study by Fama and French (2008) explores various cross-sectional return predictors and shows 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 (suggested by Fama, 1998) that technologies and policies that reduce trading frictions facilitate market efficiency.

This paper is organized as follows. Section I presents the list of anomalies we consider. Section II describes the data. Sections III and IV consider portfolio and regression approaches, respectively. Section V considers the role of liquidity in the attenuation of anomalies, while Section VI considers explicit rationales for attenuation. Section VII concludes.

I. The Anomalies

Our primary aim is to explore how cross-sectional predictability has changed over time as stocks have become more liquid and more actively traded. Our hypothesis is that as markets become more liquid and as trading costs decline, increased arbitrage activity would lead to a decline in cross-sectional predictability.

The firm characteristics included in our analyses 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 measure of illiquidity. The Amihud (2002) illiquidity measure is the average daily price impact of order flow and is computed as the absolute price change per

dollar of daily trading volume: $ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} * 10^6$, 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.[4] While there are rational reasons for liquidity to be priced, Baker and Stein (2004) suggest that liquidity may be a sentiment indicator, indicating that the liquidity effect may be arbitrageable.

7) SUE: the 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 the earnings surprise to evaluate the impact of the post-earnings-announcement-drift (PEAD) as in Bernard and Thomas (1989, 1990), and Ball and Brown (1968).
8) ACC: accounting accruals, as measured in Sloan (1996), is 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.
9) IVOL: idiosyncratic volatility, as in Ang, Hodrick, Xing and Zhang (2006), is computed as the standard deviation of the regression residual of the Fama and French (1993) three-factor model using daily data within a month.
10) AG: asset growth, as in Cooper, Gulen and Schill (2008), is computed as the year-on-year percentage change in total assets.
11) PROFIT: profitability, as in Fama and French (2006), is calculated as earnings divided by book equity, where earnings is defined as income before extraordinary items.

[4] Though there are other measures of liquidity, the Amihud measure 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).

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

In part of our study we split the sample by the Amihud (2002) measure of illiquidity, since there is evidence that liquid and illiquid segments of the stock market may have experienced different degrees of illiquidity declines in recent years (Ball and Chordia, 2001); we examine whether they also exhibit heterogeneous changes in cross-sectional return predictability. Finally, 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.

II. 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 Nasdaq volume (required for computation of turnover and the illiquidity measure) is not available prior to this date.[5] To be included in the monthly analysis, a stock has to satisfy the following criteria: (i) its return in the current month and over at least the past six months has to be available from CRSP, (ii) sufficient data have to be available to calculate market capitalization and turnover, and (iii) adequate data have to be available on Compustat to calculate the book-to-market ratio as of December of the previous year. In order to avoid

[5] 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 thus 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 if increased liquidity and trading activity facilitates arbitrage (by allowing arbitrageurs trade more cheaply and camouflage their trades more effectively) and, in turn, impacts cross-sectional predictability.

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 for the characteristics in the full sample. Nasdaq firms are smaller, less liquid, more idiosyncratically volatile, less profitable, and, on net, issue more shares than NYAM ones. Note also that the measured Nasdaq turnover is higher than that in 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 a regression analysis.

III. Portfolio Results

In this section, we first present the results of a portfolio analysis that consider the long-short return spread formed by sorting on the various anomalies, and then consider a composite portfolio strategy that combines the anomalies.

A. Hedge Portfolio Returns

We first examine the profitability of portfolios sorted on the two-period lagged values of the different characteristics. We examine the profitability of extreme decile portfolios that are long the high characteristic values and short the low characteristic values.[6] Note that this exercise

[6] Instead of long-short portfolios based on extreme deciles, we also examine zero-net-investment relative strength portfolio strategies that use all stocks in the cross-section (see Lehmann, 1990, p. 8, for methodological details on

does not account for the fact that some of the anomalies may be related. We address this issue via a regression analysis that accounts for marginal effects of each anomaly in the next section. For now, in Table 2, we provide the (equally-weighted) average 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 the post-earnings-announcement-drift (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.

Turning to Nasdaq stocks, we find that size, reversals, and turnover are not significant at the 10% level, whereas all other anomalies are significant at this level, and the return magnitudes

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the relative strength portfolios). These strategies tend to take long positions in stocks with higher (lower) values of characteristics that positively (negatively) predict returns and short positions in the remainder of the stocks. The results obtained from these strategies are similar to those presented here. We illustrate the relative strength approach and apply it to a composite portfolio strategy that incorporates all of our anomalies in Section III.C to follow.

are quite comparable to those of NYAM stocks. Overall, we conclude that most of the anomalies are robust and persist in NYAM as well as Nasdaq stocks.

B. Trends in the Long-Short Portfolio Returns

In this subsection, we test the null that anomaly profits have not attenuated over time against the alternative of attenuation. In order to perform this test, we use the simple approach of fitting a trendline through the time series of hedge portfolio returns. [In Section VI, we conduct other tests, including splitting the sample in half, and dividing the sample into pre- and post-decimalization periods.]

Table 3 provides the coefficients of the linear time trend. The coefficient estimate on the time trend for the NYAM portfolio returns formed by sorting on the past one month return (reversal strategy) is 0.61×10^{-4}. Since the return from buying (selling) stocks with low (high) past one month return from Table 2 is -0.5%, 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 -0.51×10^{-4}. Since the return to the momentum strategy is positive, a negative coefficient signifies a decline in profits over time.

More generally, we define an attenuation as a situation where the trend is in the opposite direction of the baseline effect (for example, a positive trend for accruals and a negative trend for profitability implies attenuation). The NYAM trend coefficient estimates suggest an attenuation in anomaly-based trading profits over time for almost all the anomalies (exceptions being idiosyncratic volatility and profitability). Under the binomial distribution where attenuation or accentuation is equally likely, we note that the p-value for ten attenuations in 12 trials under the binomial distribution is 0.02, and the 10% significance cutoff is nine attenuations out of 12. Thus, more anomalies show attenuation than would be expected by chance. In the remainder of the paper, we will implicitly use these binomial cutoffs at several points without explicitly restating them.

Recall that our hypothesis is that anomalies should have *declined* in recent years with 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 appear in the last column of Table 3. As can be seen, many p-values are below 0.1 but fewer are below the 0.05 threshold. We propose that the 0.1 cutoff is more appropriate for our purposes. This is because a higher significance cutoff is appropriate when the cost of a Type II error is high. In our context, a Type II error is falsely accepting that the market has remained inefficient in recent years (the null) when in fact anomaly profits have attenuated towards zero. A naïve investor that incurs trading costs to futilely bet on anomalies commits a Type II error, and this error can be very costly to such investors because it leads to resource misallocation.[7] Based on these arguments suggesting a higher cost of a Type II error from the perspective of a naïve investor, we use the 0.1 cutoff in the paper's exposition, but also provide the accompanying p-values.

[7] On the other hand, rejecting the null of no attenuation when in fact there is (a Type I) error is arguably not that costly for a naïve investor, as the course of action in this case would be to invest in a passively-managed portfolio and save on transaction costs (and many anomalies incur high transaction costs because of the need to short-sell—viz. Stambaugh, Yu, and Yuan, 2012).

We see from Table 3 that there is a significant decline in the profitability of nine of twelve anomalies for NYAM stocks.[8] The exceptions are asset growth, idiosyncratic volatility, and profitability. The picture for the less liquid Nasdaq stocks is different. We find that while ten of twelve anomalies attenuate, only four (value, momentum, profitability, and SUE) demonstrate significant attenuation at the 10% level. Overall, therefore, we can conclude that there is somewhat stronger evidence of attenuation in the more liquid NYAM stocks.

In Table 3, we also provide the number of significant *accentuations* (at the 10% level, i.e., the number of trend coefficients with a *p*-value exceeding 0.9). Note here the asymmetry in significant attenuations and accentuations. While nine anomalies have significantly attenuated for NYAM stocks only one anomaly has significantly accentuated (the *p*-value exceeds 0.9 in only one case—that of the profitability anomaly), and out of a sample of 12, one significant coefficient can be attributed to chance. Further, for Nasdaq stocks, none of the anomalies have significantly accentuated. Thus, the overall picture is quite consistent with attenuation in anomaly profits over time.

C. A Composite Trading Strategy

In addition to considering the characteristics separately, we also construct a composite portfolio strategy that uses all of the characteristics as follows. Each month, we rank stocks by the value of a particular characteristic, say book/market, and assign the rank value to the stock. For size, monthly reversals, turnover, accruals, asset growth, new issues, and asset growth, which negatively predict returns, we sort in reverse order before assigning ranks. At the end of this

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

exrcise, we have twelve ranks for each stock, each corresponding to a different characteristic. We then divide each rank value by the cross-sectional sample size to get a percentile rank. Finally, we average the percentile rank across characteristics for each stock. This average percentile rank forms the composite characteristic, which is then used to compute the relevant portfolio weights as follows.

Given a percentile rank characteristic Z_{it} for stock i at time t, with cross-sectional mean $\overline{Z}_t$, define the weights on each stock at time t to be

$$w_{it} = [Z_{it-2} - \overline{Z}_{t-2}] / \sum_{[Z_{it-2} - \overline{Z}_{t-2} > 0]} [Z_{it-2} - \overline{Z}_{t-2}]. \tag{1}$$

This strategy is one dollar long and one dollar short on Z, measured for security i at time $t-2$. That is, it places an aggregate bet of one dollar long (short) on those stocks whose percentile rank is above (below or equal to) the cross-sectional mean percentile rank. To see this, first note that the weights in Eq. (1) sum to zero in the cross-section, because the numerator on the right-hand side of the equation sums to zero (the denominator cannot be zero). Second, the weights trivially sum to one for stocks for which the condition under the summation sign is satisfied (i.e., for which $Z_{it-2} - \overline{Z}_{t-2} > 0$), so that the strategy is one dollar long on stocks where the characteristic exceeds its cross-sectional mean. Since the weights sum to zero, it follows that the strategy is one dollar short on stocks where the characteristic is at or below its cross-sectional mean.

The above weighting scheme uses all stocks in the cross-section while placing a larger weight on stocks with the more extreme percentile ranks. The monthly return on this strategy at time t is calculated as a weighted average using the weights as calculated above:

$$R_t = \sum_i w_{it} R_{it}. \qquad (2)$$

where R_{it} is the raw return for stock i in month t. Since we use raw returns, the composite portfolio results do not depend on any specific model of risk adjustment.

Results for this composite strategy appear in Panel A of Table 4. The monthly return to the composite strategy for NYAM stocks is 1.20% and strongly significant, suggesting strong profits to a composite anomaly-based trading strategy. In Panel B of Table 4, we report results from regressing the composite profits on a time trend. We observe a clear downward trend to the composite strategy profits for NYAM stocks. For Nasdaq stocks, we find from Panel A that the profitability of the composite strategy is higher at 2.0% per month than that for NYAM stocks, and the trend coefficient in Panel B, while demonstrating attenuation, is less significant than for NYAM stocks (though its point estimate is similar).

IV. Regression Analysis and Results

Since a number of the anomalies may be related, it is important to assess each anomaly's marginal impact after controlling for the effects of the others. To address this issue, we now turn to multivariate Fama-MacBeth (1973) regressions where we estimate the reward for exposure to each security characteristic. As in the previous section, our approach is to first present the coefficients for the full sample period and then examine evidence of attenuation over time.

A. Regression Methodology

Our empirical method 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. This approach avoids the data-snooping biases that are inherent in portfolio-based approaches (see Lo and MacKinlay, 1990). Moreover, the use of individual stocks as test assets avoids the possibility that tests may be sensitive to the portfolio grouping procedure.

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

$$R_{jt}^{*} = R_{jt} - R_{Ft} - \sum_{k=1}^{K} \quad {}_{jkt-1} F_{jk} \quad , \tag{3}$$

where β_{jkt-1} is the beta estimated for each stock by a first-pass time-series regression over the entire sample period.[9] The Fama-French (1993) factors are used to adjust for risk. The risk-adjusted returns are then regressed on the equity characteristics:

$$R_{jt}^{*} = c_{0t} + \sum_{m=1}^{M} c_{mt} Z_{mjt-k} + e_{jt}, \tag{4}$$

where Z_{mjt-k} is the value of characteristic m for security j at time t-k, with M being the total number of characteristics. Thus, the characteristics are lagged by k periods; $k=2$ for all characteristics (following BCS) except for reversals where $k=1$. 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 (1973) estimators are the time-series averages of the regression coefficients, $\hat{c}_t$. While we use the risk-adjusted returns from Eq. (4) throughout the paper to estimate the

[9] 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.

regression coefficients, the results (available upon request) are substantially similar when we use raw returns.

B. Basic Regression Results

In Table 5, we use the methodology of the previous subsection to estimate the Fama-MacBeth coefficients for our twelve anomalies; these coefficients represent the reward for exposure to the anomaly-based characteristics. (Henceforth, we will refer to these coefficients as "characteristic premiums.") We present results separately for NYAM and Nasdaq stocks.

The results are as expected given the anomalies literature. Monthly reversals, momentum, firm size, book-to-market ratio, illiquidity, accruals, asset growth, new issues, idiosyncratic volatility, profitability (of marginal significance) and PEAD all 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 0.15% decrease in stock returns per month. Also, a one standard deviation increase in the past one month return causes a 0.36% decrease in returns per month.

For Nasdaq stocks, the results are similar. Every anomaly, except turnover and profitability is significant. The characteristic premiums for Nasdaq stocks are by and large of a magnitude comparable to that for NYAM stocks. Overall, the results in Table 5 suggest that even after accounting for the marginal effect of other anomalies, each anomaly exerts a significant influence on the cross-section of returns.

C. Trends in the Fama-MacBeth coefficients

In Panel A of Table 6, we formally test whether there has been a decline in the FM coefficients for the anomaly-based characteristics by regressing the coefficients on a linear time trend and providing *p*-values for the attenuation test. Again, we perform the analysis separately for NYAM and Nasdaq stocks.

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For NYAM stocks, the coefficient on the time trend of the monthly reversal based characteristic premium is positive and highly significant. As the FM coefficients on the reversal strategy are negative (since in the cross-section, higher returns last month lead to lower returns this month) a positive time trend points to a reduction in the profitability for the reversal strategy. The characteristic premiums on momentum have a declining time trend. This is also consistent with declining profitability for momentum because higher past returns over the period *t*-2 through *t*-12 lead to higher returns in the cross-section. Similarly, the negative characteristic premium on firm size with a positive time trend; the negative characteristic premium on idiosyncratic volatility with a positive time trend; and the positive characteristic premium on standardized unexpected earnings (SUE) with a negative time trend, all point to a decline in the profitability for these anomalies over time. The (absolute) characteristic premium for the accruals anomaly also declines over time.

Overall, all but two anomalies (illiquidity and asset growth) attenuate for NYAM stocks, more than that expected by chance alone. When we test for attenuation, six NYAM characteristic premiums (those for size, monthly reversals, momentum, accruals, IVOL, and SUE) exhibit a significant declining trend (at the 10% level, we would expect only one attenuation via chance alone). In contrast, for the Nasdaq results in the last three columns, we find that only momentum, reversals, and illiquidity exhibit significant evidence of attenuation. Note that there is just one case of significant accentuation (NYAM illiquidity) out of 24 cases (12 each for NYAM and Nasdaq).

In sum, for NYAM stocks, ten of 12 anomalies attenuate (six significantly), and just one accentuates, suggesting a picture consistent with attenuation of anomalies over time in the liquid NYAM stocks. For Nasdaq stocks, only three of 12 anomalies accentuate significantly, and none accentuate significantly. Also note that the return to the composite portfolio strategy in Panel B of Table 4 demonstrates attenuation for both NYAM and Nasdaq, but the *p*-value points to greater statistical significance for NYAM stocks.

The preceding results are consistent with the notion that anomalies have by and large attenuated, and have attenuated more for the relatively larger and more liquid NYAM stocks (viz. Table 1). To examine the NYAM attenuation in more detail, we plot in Figure 1 the trend in the characteristic premiums for firm size, reversals, momentum, idiosyncratic volatility, PEAD, and accruals (the six variables in Table 6, Panel A, that show a significantly attenuated trend relative to the null of no trend). Figure 2 shows the time trend in the NYAM composite portfolio returns (viz. Section III.C) based on all twelve anomalies that we consider. In these plots, we use five-year moving averages of the Fama-MacBeth coefficients and the composite returns, respectively, to reduce noise in the monthly series. The figures indicate that the decline in the plotted characteristic premiums and the overall profitability of the anomaly based trading strategies is fairly steady and does not appear to be episodic in nature. For example, the moving average monthly returns to the composite portfolio strategy decline steadily from about 2% at the beginning of the sample period, to about 1% in 2000, to less than 0.5% by the end of the sample period.

V. The Role of Liquidity

The preceding results suggest attenuation in anomaly profits, more so for NYAM stocks than for Nasdaq stocks. To investigate this further, we now split the former sample into stocks with high and low liquidity. We do this by dividing stocks each month into two groups, which represent above-median and below-median values of the Amihud illiquidity measure at time *t*-2. The idea is to test (i) whether the anomaly based trading strategy profits are higher for the illiquid stocks and (ii) whether the anomalies have attenuated more for the liquid stocks. To motivate (ii), we note that the improvement in liquidity in recent years has been larger for the more liquid stocks. Indeed, the value weighted Amihud illiquidity measure declined by 85% (72%) for the NYAM liquid (illiquid) stocks in the second half of our subsample (1994-2011) relative to the first half. This is consistent with Chordia, Sarkar, and Subrahmanyam (2011) who show that larger, more liquid stocks have experienced a much steeper decline in spreads in recent years than smaller, less liquid ones. The analysis of Ball and Chordia (2001) suggests that this is primarily because the tick size was more binding for more liquid NYAM companies, so that decimalization had a more dramatic impact on their spreads.[10]

[10] A split of Nasdaq stocks by liquidity does not lead to any substantive insight, primarily because the vast majority of Nasdaq stocks are less liquid to begin with, so that the tick size is less binding for such stocks (basically the more liquid Nasdaq segment is similar in liquidity properties to the illiquid NYAM segment) and does not show much evidence that the characteristic premiums have attenuated over time. Also, when we follow Gao and Ritter (2010) and use the NYSE illiquidity breakpoints to separate the Nasdaq stocks into liquid and illiquid samples, we find that there are on average 1322 stocks per month in the illiquid Nasdaq sample and only 243 in the liquid sample. We do not report these results in our analysis, but they are available upon request.

In Table 7, we examine the trend in the Fama-MacBeth coefficients separately for liquid and illiquid stocks. We find that the declining trend in the characteristic premium estimates is more prevalent amongst the liquid stocks. Thus, from the trend regressions amongst the liquid stocks, we see that the characteristic premiums move towards zero over time, for size, BM, reversals, momentum, accruals, new issues, idiosyncratic volatility, profitability, and SUE, i.e., nine of twelve anomalies, and all of these anomalies except size attenuate significantly (i.e., there is significant evidence of attenuation in eight of twelve cases). For the illiquid stocks, while eight anomalies attenuate, there are significant attenuations only for reversals, momentum, idiosyncratic volatility, firm size, and SUE, i.e., for five of twelve cases.

Overall, there is a contrast in the behavior of the characteristic premiums across the liquid and illiquid stocks, and stronger evidence of anomaly attenuation in the liquid stocks, amongst which there has been a larger improvement in liquidity over time. The fact that the characteristic based profitability declines more strongly for the liquid stocks suggests that arbitrageurs have become more active in the liquid stocks as the cost of trading in these stocks declines and their trades lead to a decline in the profitability.

We now turn to the returns for the composite portfolio defined in Table 4, computed separately for liquid and illiquid stocks. In results not reported in a table for brevity, we find that the full sample composite return for the liquid (illiquid) stocks from a composite trading strategy is 0.75% (1.42%) per month. Thus, the composite portfolio yields returns for illiquid stocks that are almost twice as high as those for the liquid stocks and we have verified that the difference is economically and statistically significant.

In the last row of Table 7, we present results from a trend fit to the composite portfolio strategy for liquid and illiquid stocks. The trend fit indicates that the profits have attenuated towards zero for both liquid and illiquid stocks. While the trend is significant for both liquid and illiquid stocks, we have verified that for liquid stocks the portfolio returns attenuate from a significant 1.09% in the first half of the sample period (1976-1993) to an insignificant 0.42% in the second half (1994-2001), whereas the returns for illiquid stocks attenuate from a significant 1.9% to a significant 0.95% in the second half. Thus, for liquid stocks the composite portfolio returns are statistically indistinguishable from zero in the second half of the sample period whereas for illiquid stocks they remain significant.

Overall, the number of attenuations (nine of 12), the number of significant attenuations (8 of 12), the virtually complete lack of significant accentuations (just one of 12), and the strong attenuation in the composite portfolio returns, all suggest a picture consistent with attenuation of anomalies over time in the liquid NYAM stocks.

One concern is that our results may be driven by the financial crisis. On the other hand, a confounding issue in explicitly considering the crisis is that ex post consideration of events could be viewed as arbitrary. Nevertheless, we address the possible impact of the financial crisis on our results by dummying out the crisis period of December 2007 to June 2009 in the trend regressions.[11] While this causes a loss of observations, all of our central conclusions on the

[11] "The US recession began in December 2007 ended in June 2009, according to the U.S. National Bureau of Economic Research (NBER)"—(http://en.wikipedia.org/wiki/Financial_crisis_of_2007-2008).

number of attenuations and the number of significant attenuations are largely unaltered by this exercise.[12] We do not report these results here for brevity, but details are available upon request.

VI. Sources of the Decline in Anomaly Profits over Time

There are a number of possible reasons for the evidence of a decline in the anomaly profits over time.

1. Change in the risk-return trade-off. It is possible that the decline in the anomaly profits 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, we note that many of the considered return predictors show a decline. It seems unlikely that the nature of shifts in risk pricing could cause such a wide-ranging decline, especially since a risk-based rationale for many of the predictors (especially variables such as accruals and one-month reversals) has been elusive. Therefore, it seems daunting to attempt to attribute our results to shifts in risk pricing.
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.

[12] Consistent with Daniel, Jagannathan, and Kim (2012), the most relevant impact of the crisis is on momentum. The trend coefficient for liquid stocks declines (in absolute terms) from –0.464 to –0.297 (-0.484 to –0.327) for liquid (illiquid) stocks after dummying out the crisis. But all four of these attenuations remain significant.

We now address the second and third rationales provided above using the NYAM sample, as that is where the attenuation in anomalies is more evident. First, 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.[13] 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 8 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 of the characteristic premium has declined from -0.128% from before its discovery to -0.066% (still statistically significant) to after its discovery. The characteristic premium on reversals has declined but it is still statistically significant. The characteristic premiums of momentum, turnover, and accruals show a decline after their discovery. 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 profitability. The characteristic premiums for illiquidity and profitability have

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

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.[14] The coefficients suggest post-discovery attenuation in only five of eleven cases (not a significant number), and four of these cases are significant.[15]

Overall, the results are mixed. The characteristic premiums for firm size, reversals, momentum, turnover and accruals have declined from before to after their discovery. However, the premiums for BM, idiosyncratic volatility, illiquidity, profitability, asset growth, new issues, and SUE have not declined after their discovery, suggesting that data mining is not a likely rationale for the anomalies.

We now turn to an examination of the possibility that increased turnover and liquidity could have facilitated the attenuation of anomalies via increased arbitrage. First, in order to examine the impact of the increased turnover in the post-1993 period (Chordia, Roll, and Subrahmanyam, 2011), we divide the sample into two equal sub-periods: 1976-1993 and 1994-2011. The Fama-MacBeth results appear in Panel B of Table 8. We find that size, reversals, momentum, idiosyncratic volatility and SUE, 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 SUE is

[14] Our results for BM, idiosyncratic volatility, illiquidity, profitability, asset growth and new issues are not completely consistent with the conclusion of McLean and Pontiff (MP) (2011) that academic research attenuates anomalies. But our study and that of MP are not directly comparable; we consider anomalies separately, whereas MP consolidate anomalies and report only aggregate results.

[15] The before/after comparisons in Panel A of Table 8 and in Panels B and C to follow involve a straightforward computation of differences-in-means and the associated standard errors.

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 0.38% (0.03%) in the first (second) sub-period.[16] Similarly, a one standard deviation increase in SUE results in an increase in monthly returns of 0.16% (0.05%).[17] Moreover, the above monthly returns to momentum and SUE are statistically insignificant in the second sub-period.

We further observe that the (absolute) estimates of the characteristic premiums are lower in the second sub-period in all cases with just three exceptions (out of twelve), and this is a significantly higher number of attenuations than due to chance alone. The three exceptions are the asset growth anomaly and 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) as well as illiquidity, which puzzlingly provides statistically significantly (at the 10% level) higher returns in the second sub-period. We observe that while nine of twelve anomalies attenuate, the attenuation in anomalies is significant in five of 12 cases. The last row of Panel B compares the return on the composite portfolio considered in Table 4 across the first and second sub-periods. We find that the return decreases from an average of 1.63% per month in the first half of the sample to 0.76% per month in the second half, and this decrease is strongly significant. Again, the large number of attenuations and the virtual complete lack of accentuations is consistent with overall attenuation in the anomalies.

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[16] Novy-Marx (2012) also finds a decline in the Fama-Macbeth coefficients for momentum in the recent period, when considering the post-war sample.

[17] Since the FM coefficients do not capture the dollar impact, it is important to examine the change in the economic significance from the first sub-period to the second. We note here that the economic significance, as computed by multiplying the FM coefficients by the average standard deviation of the characteristic in the relevant subperiod, declines in the second sub-period (relative to the first) for nine out of the twelve anomalies that we consider.

Note that the regressions above do not address specific rationales for attenuation in the anomalies. To address this issue we try different identification schemes: (i) exogenous decrease in the tick size due to decimalization, (ii) assets under management of hedge funds, and (iii) short interest. These variables are proxies for arbitrage activity.

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) 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 8 show that except for illiquidity, the characteristic premiums have declined towards zero for all the anomalies (eleven of 12, even higher than that in Panel B), though only five of 12 anomalies show a statistically significant attenuation at the 10% level. Observe though that after decimalization, except for the premium on illiquidity, none of the characteristic premiums are statistically significant at the 5% level. Further, the sole accentuation amongst the twelve anomalies post-decimalization (illiquidity) is not significant. Overall, while the lack of significant attenuations can possibly be attributed to fewer observations in the post-decimal period, attenuation in the point estimate of eleven of 12 anomalies (as in Panel C) is unlikely to arise from chance alone.

Note also that the impact of firm size, reversals and idiosyncratic volatility continues to be significant after their discovery (Panel A of Table 8) but none of these anomalies are statistically significant after decimalization. Further, for all three cases, the point estimates of the characteristic premiums are lower in absolute terms after decimalization. In unreported analysis, we find that economic significance, defined as the Fama-MacBeth coefficient multiplied by the average monthly standard deviation of the characteristic, declines in nine of twelve cases (including firm size, reversals and idiosyncratic volatility) after decimalization. This is consistent with the notion that decimalization is associated with a reduction in the characteristic premiums after accounting for the post-discovery effect.

In the last row of Panel C, we also compare the return on the composite portfolio considered in Table 5 pre- and post-decimalization. We find that this return more than halves in magnitude from an average of 1.5% per month before decimalization to 0.6% per month after decimalization (both numbers remain significant). Further, this decrease of 0.9% is significant with a *p*-value of 0.003.[18] These results also indicate that profits from anomalies in the post-decimal period have been harder to come by.

Next, we consider assets under management for hedge funds (AUM), scaled by the previous month's value-weighted market capitalization for NYAM stocks.[19] 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 anomaly-based profits. Since shorting is an important component of arbitrage, we also use the monthly short interest for our sample period as a fraction of the previous month's

[18] Our results are different those in Israel and Moskowitz (2012), possibly because we focus on the dramatic decline in trading costs and the increase in trading activity that has occurred in the more recent years.

[19] We thank Matti Suominen and LIPPER-TASS for data on hedge fund flows. 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. An alternative to AUM is flows to hedge funds, but this latter variable does not play a major role in explaining trends in anomalies (results using hedge fund flows are available upon request).

outstanding shares to proxy for arbitrage activity. Panel D of Table 8 shows the results from regressing the monthly Fama-MacBeth coefficients on the one-month lagged and logged AUM and value-weighted average of the short interest on NYAM stocks.

The characteristic premiums of firm size, reversals, momentum, accruals, idiosyncratic volatility, and SUE decline significantly with an increase in AUM, whereas those for reversals, size, reversals, momentum, accruals,[20] and profitability decline significantly with an increase in short interest, suggesting that hedge fund growth and shorting activity have indeed led to a decline in the profitability of the anomaly based trading strategies. As many as nine (eight) the twelve coefficients on AUM (short interest) are of a sign that indicates that increases in AUM (short interest) are associated with attenuation in the anomalies, and six each are significant at the one-tailed 10% level, and only *one* characteristic (illiquidity) is associated with accentuation. In the last row of Table 8, we also provide returns for the composite portfolio strategy and these attenuate significantly with an increase in hedge fund assets under management as well as aggregate short interest.

In economic terms, a one standard deviation change in AUM changes the characteristic premium of firm size by 0.00038. From Table 5, the full-sample characteristic premium of size is -0.00076. So a one standard deviation increase in AUM results in the approximate halving of the (absolute) characteristic premium for firm size, and, similarly, a decline of 50% for reversals, 80% for momentum, 70% for accrual, 60% for idiosyncratic volatility and 50% for PEAD. Using analogous arguments, we find that a one standard deviation increase in the aggregate value-

[20] Green, Hand, and Soliman (2011) also argue that the decline in the profitability of the accrual based trading strategy is due to an increase in the capital invested by hedge funds into exploiting it. See also Richardson, Tuna, and Wysocki (2010).

weighted short interest more than halves the premium for profitability, momentum, and idiosyncratic volatility, reduces the size premium by 40%, and decreases by about 30% the premium for reversals. Overall, the results do provide some evidence that the proxies for arbitrage trading – short interest, hedge fund assets under management and the exogenous decline in trading costs have led to a decrease in anomaly-based cross-sectional predictability of returns.

VII. Summary and Concluding Remarks

We study several equity market anomalies over more than three decades, and find diminished cross-sectional return predictability during recent years, especially for liquid NYSE/AMEX (NYAM) stocks. Several anomalies have attenuated over time, and just one or two have accentuated. A composite portfolio strategy exploiting these anomalies shows markedly decreased profitability in recent years.

There are a few potential reasons for the general decline in the profitability of the anomaly based trading strategies. One reason could be that our results are picking up some change in the nature of risk pricing in the economy. While this argument cannot be fully ruled out, we note that many of the return predictors show a decline, and it is hard to argue for a risk-based rationale across so many of the anomalies. A second reason could be that the anomalies have been discovered due to data mining exercise and that their impact on returns would disappear upon discovery. However, we find that the point estimates of the characteristic premiums for BM, idiosyncratic volatility, illiquidity, profitability, asset growth, new issues, and PEAD have not appreciably declined after their discovery, while data mining would suggest such a decline.

This leaves us with the rationale that at least some portion of the anomaly returns are arbitrageable and such arbitrage has increased in recent years.

In order to establish a link between increased arbitrage activity to the decline in the profitability of the anomaly based trading strategies we examine (i) the impact of the decline in the tick size to decimals and (ii) the impact of hedge fund assets under management and short interest on the anomaly based predictability. The exogenous decline in the tick size to a penny resulted in improvements in liquidity and 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 composite anomaly-based portfolio have declined by more than half in the post-decimal period. Moreover, the impacts 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 the hedge fund assets and/or short interest, 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 post-decimalization 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. Indeed, this observation may explain why the statistical significance of the attenuation in our analysis is modest in several cases. Nonetheless, 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.

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Table 1: Summary Statistics

This table presents the time-series averages of the cross-sectional means, medians, and standard deviations of the variables. Size represents the market capitalization in billions of dollars. The NYSE/AMEX (NYAM) sample period is 1976-2011, whereas the Nasdaq sample period is 1983-2011. The average numbers of firms per month for NYAM and Nasdaq stocks are 1422 and 1565, respectively. BM is the logarithm of the book-to-market ratio. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. Turnover is the monthly share trading volume divided by shares outstanding. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). ISSUE represents new issues as in Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). PROFIT is the profitability as in Fama and French (2006). SUE is the 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.

	NYAM			Nasdaq		
Variable	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
SIZE ($ billions)	2.580	0.542	6.265	0.702	0.115	3.287
BM	0.836	0.686	0.681	0.682	0.513	0.655
R1	0.012	0.005	0.113	0.014	-0.002	0.169
R212	0.167	0.105	0.435	0.199	0.062	0.638
TURN	0.086	0.065	0.078	0.134	0.083	0.157
ILLIQ	0.081	0.004	0.363	0.218	0.015	0.930
ACC	-0.032	-0.035	0.080	-0.032	-0.032	0.107
AG	0.143	0.072	0.480	0.261	0.090	0.935
ISSUE	0.024	0.004	0.117	0.049	0.010	0.153
IVOL	0.021	0.017	0.013	0.033	0.029	0.020
PROFIT	0.061	0.116	0.428	-0.111	0.065	0.758
SUE	-0.087	0.106	2.024	-0.115	0.080	2.228

Table 2: Hedge Portfolio Returns

This table presents the average percentage returns along with t-statistics for the long and the short decile portfolios formed on the anomalies of interest. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. Turnover is the monthly share trading volume divided by shares outstanding. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). ISSUE represents new issues as in Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). PROFIT is the profitability variable as in Fama and French (2006). SUE is the 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.

	NYAM		Nasdaq	
	mean	t-stat	mean	t-stat
SIZE	-0.559	-2.10	0.003	0.01
BM	0.997	5.15	1.505	5.28
R1	-0.502	-2.37	-0.257	-0.81
R212	1.439	4.61	1.882	5.02
TURN	-0.493	-2.34	-0.458	-1.09
ILLIQ	0.516	2.17	0.533	1.66
ACC	-0.330	-2.84	-0.553	-3.66
AG	-0.551	-4.19	-0.434	-2.56
ISSUE	-0.930	-7.60	-1.553	-6.35
IVOL	-0.637	-2.03	-1.475	-3.91
PROFIT	0.168	0.90	0.877	3.18
SUE	0.739	6.65	0.990	7.94

Table 3: Trend Fits to Hedge Portfolio Returns

We run linear regression of the hedge portfolio returns on time and this table reports the slope of the linear regression with associated t-statistics. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. Turnover is the monthly share trading volume divided by shares outstanding. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). ISSUE represents new issues as in Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). PROFIT is the profitability as in Fama and French (2006). SUE is the 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. The coefficients for the time trend is multiplied by 10000. The *p*-values are for the one-tailed test that the anomaly has attenuated over time. * (†) denotes a *p*-value less than 0.1 (greater than 0.9).

	NYAM		Nasdaq	
	Trend	Attenuation *p*-value	Trend	Attenuation *p*-value
SIZE	0.345	0.053*	-0.283	0.831
BM	-0.232	0.067*	-0.664	0.009*
R1	0.605	<0.001*	0.170	0.295
R212	-0.514	0.020*	-0.741	0.023*
TURN	0.231	0.085*	0.252	0.274
ILLIQ	-0.306	0.055*	-0.195	0.271
ACC	0.138	0.068*	0.116	0.221
AG	0.121	0.125	-0.087	0.695
ISSUE	0.179	0.034*	0.090	0.356
IVOL	-0.092	0.641	0.328	0.192
PROFIT	0.278	0.969†	-0.375	0.085*
SUE	-0.214	0.008*	-0.219	0.038*
Number of attenuations		10 of 12		10 of 12
(significant attenuations)		(9 of 12)		(4 of 12)
(significant accentuations)		(1 of 12)		(0 of 12)

Table 4: Composite Trading strategy

We use the method of Lehmann (1990) to document portfolio returns, where the weights are based on averaging percentile rank scores of various characteristics for each stock on portfolios. We present the percentage portfolio returns of the composite strategy with associated t-statistics. We also linear regression of the portfolio returns on time, and report the slope of the linear regression with associated t-statistics. The coefficients for the time trend are multiplied by 10000. The *p*-values are for the one-tailed test that the composite portfolio return has decreased over time.

Panel A: Average return on the composite portfolio

	Full sample composite portfolio return	
	mean	t-stat
NYAM	1.196	8.77
Nasdaq	2.010	7.79

Panel B: Trend in the composite portfolio over time

	Linear trend fit to composite portfolio return	
	Trend	Attenuation *p*-value
NYAM	-0.434	0.000
Nasdaq	-0.438	0.044

Table 5: Fama-MacBeth Regression Estimates with Excess Market Return, SMB and HML as Risk Factors

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. The dependent variable is the excess return risk-adjusted using the Fama-French (1993) model. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. Turnover is the monthly share trading volume divided by shares outstanding. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). ISSUE represents new issues as in Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). PROFIT is the profitability as in Fama and French (2006). SUE is the 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. All coefficients are multiplied by 100.

	NYAM		Nasdaq	
	mean	t-stat	mean	t-stat
Intercept	1.201	4.21	2.443	3.97
SIZE	-0.076	-3.80	-0.150	-3.06
BM	0.121	2.82	0.218	3.21
R1	-3.148	-8.00	-3.005	-8.20
R212	0.509	3.01	0.573	3.02
TURN	-0.062	-1.51	-0.038	-0.71
ILLIQ	0.932	3.85	0.765	5.03
ACC	-0.832	-2.23	-1.126	-2.87
AG	-0.168	-2.34	-0.207	-2.23
ISSUE	-0.676	-3.11	-1.043	-2.68
IVOL	-21.989	-5.96	-18.957	-6.14
PROFIT	0.196	1.95	0.030	0.18
SUE	0.054	3.80	0.041	2.45

Table 6: Trend Fits to Fama-MacBeth Coefficients

We run linear regression of the Fama-MacBeth coefficients on time, and this table reports the slope of the linear regression with associated t-statistics. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. Turnover is the monthly share trading volume divided by shares outstanding. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). ISSUE represents new issues as in Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). PROFIT is the profitability as in Fama and French (2006). SUE is the 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. The coefficients for the time trend are multiplied by 10000. The *p*-values are for the one-tailed test that the anomaly has attenuated over time. * (†) denotes a *p*-value less than 0.1 (greater than 0.9).

	NYAM		Nasdaq	
	Trend	Attenuation *p*-value	Trend	Attenuation *p*-value
SIZE	0.041	0.005*	0.018	0.359
BM	-0.018	0.302	-0.005	0.468
R1	1.649	<0.001*	1.039	0.002*
R212	-0.500	<0.001*	-0.435	0.010*
TURN	0.026	0.215	0.067	0.104
ILLIQ	0.260	0.910†	-0.235	0.061*
ACC	0.367	0.059*	0.261	0.251
AG	-0.024	0.659	0.007	0.472
ISSUE	0.152	0.192	-0.389	0.841
IVOL	10.977	<0.001*	3.737	0.111
PROFIT	-0.026	0.371	-0.017	0.460
SUE	-0.022	0.028*	-0.018	0.138
Number of attenuations		10 of 12		11 of 12
(significant attenuations)		(6 of 12)		(3 of 12)
(significant accentuations)		(1 of 12)		(0 of 12)

Table 7: Trend Fits to Fama-MacBeth Coefficients and Composite Returns, by Liquidity

We run linear regression of the composite portfolio returns (described in Table 4) and Fama-MacBeth coefficients on time, and this table reports the slope of the linear regression with associated t-statistics. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. Turnover is the monthly share trading volume divided by shares outstanding. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). ISSUE represents new issues as in Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). PROFIT is the profitability as in Fama and French (2006). SUE is the 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. Stocks are defined as liquid or illiquid if their ILLIQ measure is below or above the cross-sectional median. The coefficients for the time trend are multiplied by 10000. The last row of Panels B through D provides results for the composite portfolio strategy defined in Table 4. The *p*-values are for the one-tailed test that the coefficients or composite portfolio returns have attenuated over time. * (†) denotes a *p*-value less than 0.1 (greater than 0.9).

	Liquid NYAM stocks		Illiquid NYAM stocks	
	Trend	Attenuation *p*-value	Trend	Attenuation *p*-value
SIZE	0.005	0.436	0.063	0.075*
BM	-0.076	0.039*	0.001	0.504
R1	0.812	0.020*	2.139	<0.001*
R212	-0.464	0.001*	-0.484	<0.001*
TURN	-0.008	0.552	0.026	0.255
ILLIQ	13.82	0.862	0.189	0.826
ACC	0.535	0.034*	0.204	0.288
AG	-0.188	0.944†	0.102	0.107
ISSUE	0.436	0.014*	-0.028	0.540
IVOL	9.683	0.009*	12.370	<0.001*
PROFIT	-0.542	<0.001*	0.064	0.758
SUE	-0.028	0.005*	-0.026	0.059*
Number of attenuations (significant attenuations) (significant accentuations)		9 of 12 (8 of 12) (1 of 12)		8 of 12 (5 of 12) (0 of 12)
Composite portfolio return	-0.362	0.001*	-0.440	0.001*

Table 8: Fama-MacBeth Regression Estimates and Composite Portfolio Returns: **The Impact of Discovery, Decimalization, Hedge Funds, and Short Interest: NYAM Stocks**

Panel A (Panel C) presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates before and after the discovery of anomalies (before and after the decimalization). Panel B presents the coefficients for the first and second half of the sample period (1976-2011). The dependent variable is the excess return risk-adjusted using the Fama-French (1993) model. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. Turnover is the monthly share trading volume divided by shares outstanding. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). ISSUE represents new issues as in Pontiff and Woodgate (2008). IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). PROFIT is the profitability as in Fama and French (2006). SUE is the 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. In Panel D, we run linear regression of the Fama-MacBeth coefficients on one-month lagged (logged) aggregate hedge fund assets under management, and value-weighted short interest (scaled by the previous month's market capitalization and shares outstanding, respectively), and this table reports the slopes of the linear regression with associated t-statistics. The last row of Panels B through D provides results for the composite portfolio strategy defined in Table 4. The coefficients and returns are multiplied by 100 in all panels. In Panels A through C, the *p*-values are for the one-tailed test that the difference-in-means across the two sub-periods indicates an attenuation in the anomaly in the later sub-period. In Panel D. the *p*-values are for the one-tailed test that an increase in hedge fund AUM or short interest is associated with an attenuation in the anomaly. * (†) denotes a *p*-value less than 0.1 (greater than 0.9).

.Panel A: Estimates before and after discovery of the anomalies

	Before discovery		After discovery		
	mean	t-stat	mean	t-stat	Attenuation *p*-value
SIZE	-0.128	-3.06	-0.066	-2.93	0.097*
BM	0.121	1.92	0.122	2.06	0.505
R1	-5.136	-8.93	-1.728	-3.34	<0.001*
R212	0.954	5.41	0.065	0.23	0.004*
TURN	-0.112	-2.27	0.026	0.35	0.061*
ILLIQ	0.707	4.12	1.604	1.96	0.857
ACC	-1.116	-2.80	-0.435	-0.62	0.200
AG	-0.156	-2.23	-0.298	-0.76	0.638
ISSUE	-0.667	-2.95	-0.771	-0.95	0.548
IVOL	-21.831	-5.36	-22.969	-2.78	0.549
PROFIT	0.134	1.21	0.581	2.55	0.960
Number of attenuations (significant attenuations) (significant accentuations)					5 of 11 (4 of 11) (1 of 11)

Table 8 continued on next page

Table 8, continued

Panel B: Estimates for first and second halves of the sample

	Low share turnover (1976-1993)		High share turnover (1994-2011)		
	mean	t-stat	mean	t-stat	Attenuation *p*-value
SIZE	-0.130	-5.09	-0.022	-0.73	0.003*
BM	0.137	2.28	0.106	1.72	0.360
R1	-4.873	-9.53	-1.422	-2.47	<0.001*
R212	0.954	5.41	0.065	0.23	0.004*
TURN	-0.108	-2.01	-0.016	-0.26	0.131
ILLIQ	0.504	3.27	1.359	2.97	0.961†
ACC	-1.161	-2.57	-0.503	-0.85	0.189
AG	-0.140	-1.24	-0.195	-2.19	0.649
ISSUE	-0.575	-2.08	-0.776	-2.31	0.678
IVOL	-35.992	-7.44	-7.986	-1.47	<0.001*
PROFIT	0.244	1.40	0.147	1.46	0.315
SUE	0.086	4.77	0.022	1.02	0.012*
Number of attenuations (significant attenuations) (significant accentuations)					9 of 12 (5 of 12) (1 of 12)
Composite portfolio return	1.630	9.47	0.762	3.67	0.001*

Panel C: Estimates before and after decimalization

	Before decimals (1976-2000)		After decimals (2001-2011)		
	mean	t-stat	mean	t-stat	Attenuation *p*-value
SIZE	-0.095	-4.06	-0.035	-0.90	0.094*
BM	0.139	2.72	0.081	1.02	0.270
R1	-3.881	-9.09	-1.482	-1.78	0.005*
R212	1.021	7.00	-0.654	-1.53	<0.001*
TURN	-0.086	-1.69	-0.009	-0.13	0.186
ILLIQ	0.749	4.15	1.347	1.98	0.801
ACC	-1.287	-3.35	0.202	0.24	0.054*
AG	-0.170	-1.99	-0.162	-1.22	0.480
ISSUE	-0.766	-2.96	-0.471	-1.17	0.269
IVOL	-30.317	-7.04	-3.062	-0.45	<0.001*
PROFIT	0.211	1.60	0.162	1.16	0.400
SUE	0.057	3.50	0.049	1.69	0.405
Number of attenuations (significant attenuations) (significant accentuations)					11 of 12 (5 of 12) (0 of 12)
Composite portfolio return	1.462	9.63	0.591	2.14	0.003*

Table 8 continued on next page

Table 8, continued

Panel D: Impact of hedge funds and short interest

	Hedge Fund AUM		Short Interest	
	slope	Attenuation *p*-value	slope	Attenuation *p*-value
SIZE	0.038	0.030*	0.034	0.063*
BM	-0.006	0.448	0.015	0.622
R1	1.611	0.000*	1.146	0.004*
R212	-0.402	<0.001*	-0.411	<0.001*
TURN	0.026	0.264	0.019	0.341
ILLIQ	0.345	0.919	0.360	0.911†
ACC	0.565	0.068*	0.363	0.072*
AG	-0.007	0.536	0.000	0.500
ISSUE	0.241	0.136	0.132	0.291
IVOL	13.127	<0.001*	13.089	0.001*
PROFIT	0.007	0.524	-0.179	0.054*
SUE	-0.027	0.033*	-0.005	0.367
Number of attenuations (significant attenuations) (significant accentuations)		9 of 12 (6 of 12) (1 of 12)		8 of 12 (6 of 12) (1 of 12)
Composite portfolio return	-0.560	<0.001*	-0.870	0.030*

Figure 1: Trends in Fama-MacBeth coefficients

This figure shows the five-year moving averages of the Fama MacBeth coefficients for NYAM stocks. Size represents the logarithm of market capitalization in billions of dollars. R1 is the lagged one month return in month t-1. R212 is the cumulative returns over the second through twelfth months prior to the current month. IVOL is the idiosyncratic volatility computed as in Ang, Hodrick, Xing and Zhang (2006). SUE is the 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. ACC represents accruals, measured as in Sloan (1996). Trend lines are drawn through the moving averages.

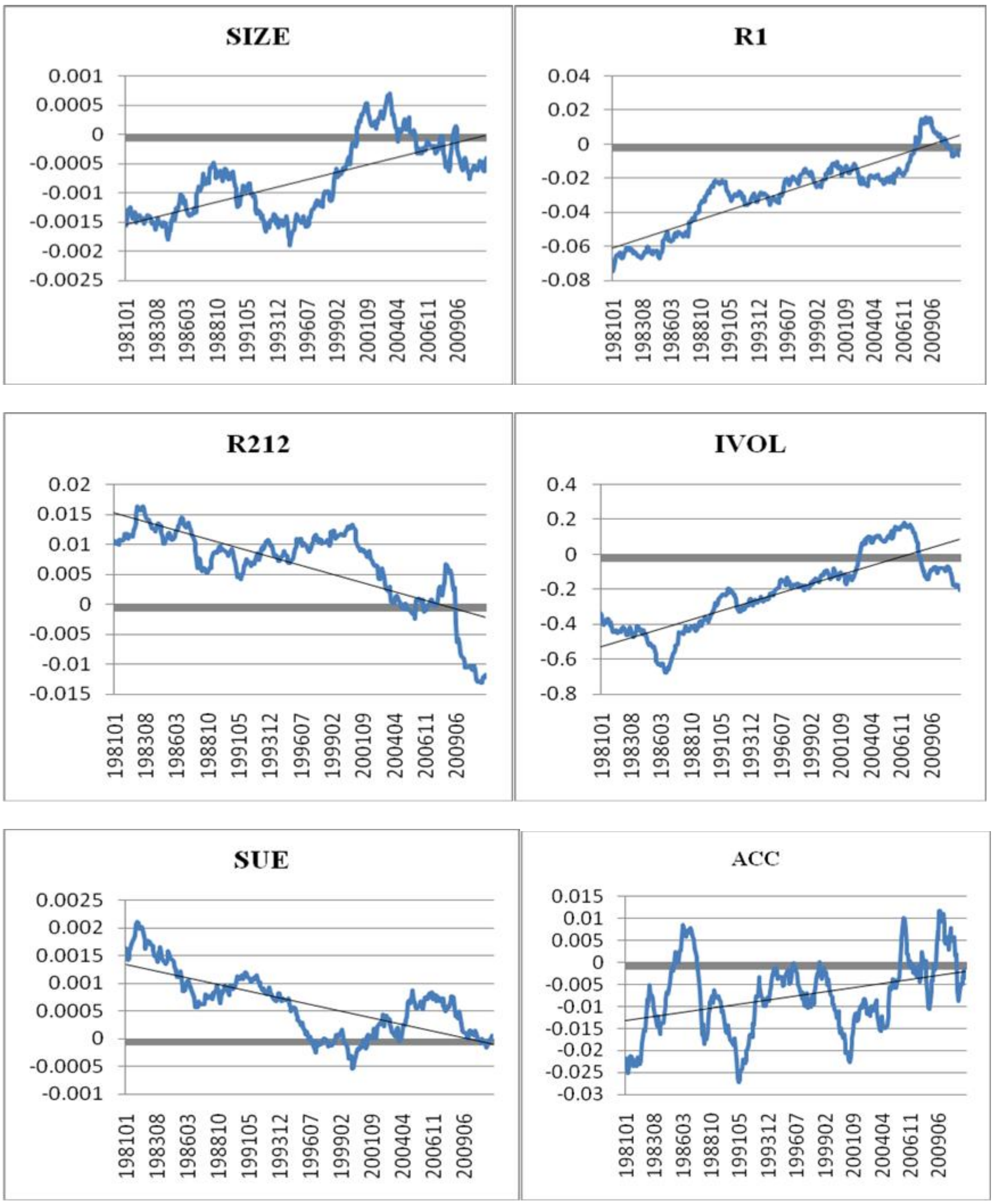

Figure 2: Trend in the Returns to a Composite Anomalies-Based Portfolio

This figure shows the five-year moving averages of the returns of the composite portfolio for NYAM stocks, based on all twelve anomalies that we consider. The composite portfolio returns are computed using the method of Lehmann (1990), where the weights are based on averaging percentile rank scores of various characteristics for each stock on portfolios.