THE POWER OF PAST STOCK RETURNS TO EXPLAIN FUTURE STOCK RETURNS

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Abstract

Researchers have long argued over whether strategies based on past stock returns have power to explain future stock returns. This paper finds no convincing evidence that either short-run or long-run contrarian strategies represent important factors for explaining the cross-section of stock returns. In contrast, the properly specified one-year momentum strategy has explanatory power for stock returns when used alone, when tested against size and book-to-market, and when subjected to exhaustive robustness checks. We conclude that one-year momentum represents a necessary third factor, along with firm size and book-to-market, for explaining the cross section of stock returns.

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I. Introduction

Many authors investigate whether there are variables that explain the cross-section of expected stock returns. Some of the variables tested include market beta [Fama and Macbeth (1973), Black, Jensen, and Scholes (1972)], leverage [Bhandari(1988)], market capitalization [(Banz(1981), Reinganum (1981)], book-to-market ratio [Chan, Hamao, and Lakonishok (1991), Rosenberg, Reid, and Lanstein (1985)], and earnings-price ratio [Basu(1983)]. Fama and French (1992) synthesize much of this work. They find that size and book-to-market are powerful explanatory variables, and furthermore, that these two measures subsume the cross-sectional power of the other variables listed above.

Past stock returns also have a long history as possible explanatory variables for future stock returns. Investment strategies such as filter rules, technical analysis, momentum investing, contrarian investing, and others, are all based on past returns. Thus, it is interesting to examine how past return based strategies fare on their own, and versus the Fama and French variables.

Researchers test a wide variety of strategies based on past returns. The strongest results are found for short-term contrarian strategies (strategies of buying losers and selling winners based on returns anywhere from one day to one month ago). Many authors find these strategies to be profitable [e.g. Jegadeesh (1990), Lehmann (1990), Conrad and Kaul (1998)]. However, others researchers [e.g. Ball, Kothari, and Wasley (1992, 1995)] challenge the short run contrarian results. This challenge is based on measurement problems induced by the bid-ask spread[1]. The controversy is unsettled.

Researchers also focus on strategies based on longer term (2-5 year) returns. DeBondt and Thaler (1985, 1987) find that contrarian strategies based on long-term returns are profitable. These long-term contrarian strategies are not as statistically strong as the short-term versions, but researchers still find them economically and statistically significant. While these results are not sensitive to bid-ask induced measurement problems, the long-term results do face their own challenge. Several authors [Chan (1988), Ball and Kothari (1989)] argue that the success of the long-term contrarian strategy is due to performance induced shifts in risk, and thus it presents no opportunity for "abnormal" profit. Chopra, Lakonishok, and Ritter (1992) disagree, finding a significant long-term overreaction effect even after adjusting for size and beta. This controversy is also unsettled.

Confusingly, Jegadeesh and Titman (1993) find a result opposite to the success of both the short and long-term contrarian strategies. They find contrarian strategies based on near-term (3-12 month) returns are not effective. Rather, it is near-term continuation (or momentum) strategies that are profitable (contrarian strategies buy past losers and sell past winners, while continuation or momentum strategies buy past winners and sell past losers).

This paper attempts to sort out these varied findings and determine whether any of the past return based strategies represent a strong source of return predictability independent of other known effects. Researchers have commonly tested past return variables in separate research, and often using different methods, from the tests of variables such as size and book-to-market. Furthermore, even the various past return based strategies have largely been tested in individually separate work. We first examine the past return based strategies in a common framework, and then use this framework to test each strategy against the non-past-return variables which other authors show to explain stock returns[2].

We confirm that past return based variables have significant power to explain future stock returns. We construct a 3-variable specification for past returns that captures and improves upon the predictability discovered by other authors. This specification includes a short-term contrarian effect (PAST(l,l) is last month's stock return), a near-term momentum effect (PAST(2,12) is last year's average monthly stock return not including last month), and a long-term contrarian effect (PAST(13,60) is the average monthly stock return over the last five years not including last year). We show that this 3-variable specification has strong and robust power to explain the cross-section of stock returns. Having established the power of these three past return based strategies, we next test the strategies against the Fama and French variables, and then examine whether our results are driven by several other effects including bid-ask induced measurement error.

The powers of both the one-month contrarian strategy and the last-year based momentum strategy are unattenuated when put in competition with the Fama and French variables. However, the success of the longer term (2-5 year) contrarian strategy is strongly related to the size and book-to-market variables. Holding size constant, and especially holding book-to-market constant, the long-term contrarian result becomes weak. Other research has focused on whether performance induced shifts in beta and/or firm size explain long-term contrarian returns. Interestingly, we find that the long-term contrarian results are most weakened in competition with book-to-market.

The success of the one-month contrarian strategy is potentially driven by bid-ask induced measurement problems. We find the one-month contrarian strategy to be considerably more powerful for smaller firms and for less liquid firms. We expect this result if contrarian returns are driven by the bid-ask spread. Also, we document a new relation between liquidity measures (e.g. trading volume), future monthly return, and last month's return. Among last month's winners, future returns are strongly positively related to liquidity measures, while among last month's losers, future returns are strongly negatively related to liquidity. Again, we expect this outcome if the bid-ask spread is driving the short-term contrarian strategy. This conditional relation is not implied if returns to short-term contrarian strategies represent either compensation for providing liquidity or true overreaction. We also examine the performance of the one-month contrarian strategy within size, price, and volume quintiles. Although the short-term contrarian strategy performs well among even the largest size quintile of firms, it is insignificant among high priced firms, and insignificant and opposite in sign among high volume firms. Finally, although testable over only NASDAQ firms, other author's find that the power of short-term contrarian strategies largely disappears when they explicitly account for the bid-ask spread [e.g. Ball, Kothari, and Wasley (1992, 1995)]. Thus, for several reasons, we believe that a large part of the power of the short-term contrarian strategy is driven by the bid-ask spread, and not a liquidity premium or true contrarian returns.

In contrast to both the short and long-term contrarian strategies, the one-year based momentum results are economically and statistically strong and suffer from neither a bid-ask problem or an attenuation problem vs. the Fama and French variables. Also, these one-year-based momentum results are not being driven by performance induced changes in firms' systematic risks, by small firm returns, by low priced firm returns, by firms with small trading volumes, by the choice of stock exchanges we sample over, or perhaps most importantly, by our choice of sample period,

We find that the time-frame chosen for defining winners and losers is absolutely crucial to the success of our near-term momentum strategy, If we include last month's return in defining winner and loser firms we risk allowing the bid-ask spread to drive our results. If we include long-term past returns, we risk allowing spurious relations between long-term past performance and size and book-to-market to drive our results. It is only recent returns (last year) that do not include very recent returns (last month) that are relatively immune from either of these effects. Defining past returns in this manner clearly leads to a successful momentum strategy. Furthermore, the robustness of this specification across sample periods reduces the risk of our results being driven by data dredging.

The main contributions of this paper are (a) defining the near-term momentum strategy as to avoid short-term bid-ask biases and long-term risk-based attenuations, (b) successfully testing this near-term momentum strategy against a wide variety of risk based (e.g. beta, size, book-to-market), and test specific (e.g. sample period) challenges, and (c) presenting serious challenges to the power of both the short and long term contrarian strategies. Our bottom line is simple. To explain the cross-section of stock returns, a third factor must be added to size and book-to-market. This factor is based on return momentum over the prior year (leaving out very recent returns). In contrast, we are doubtful that the contrarian strategies we test (based on long or short horizons) represent important factors for security returns.

This paper is organized as follows. Section II describes the data. Section III conducts simple tests (portfolio sorts) and more formal tests (Fama-Macbeth regressions) of the different past return variables' ability to explain future stock returns. Section IV examines the power of our past return variables against size and book-to-market. Section V tests if other effects (e.g. the bid-ask spread, changing systematic risk, choice of sample period, etc.) are driving the results. Section VI concludes.

II. The Data

R_{it} is the CRSP (Center for Research in Security Prices) holding period return on firm i for month t. Firms with missing returns are not included in any tests for the month in question. Also, to reduce survivorship bias, we do not include any firm in the tests until it has COMPUSTAT annual data available for the prior two years.

$\text{Log}(ME_{it})$ is the logged market value of equity for firm i during month t. ME_{it} is defined as the product of the CRSP reported price for the prior month's end and the CRSP reported number of shares outstanding for the prior month's end.

$\text{Log}(BE_{it}/ME_{it})$ is the logged book-to-market ratio for firm i during month t. BE_{it} is defined as the book value of common equity of firm i (COMPUSTAT variable 60). For calculating this ratio, both ME and BE are updated only annually (not monthly as in the version of ME_{it} defined above). Every July we form $\log(BE_{it}/ME_{it})$ from each firm's prior end of December ME_{it}, and their prior year's BE_{it}. These values are held constant for the firm until the next July. Thus, there is at least a six month lag between the actual date of the information and the date we include the information in the tests. The reason for this December to July lag is to insure that the accounting data would actually be available at the time portfolios are formed. Negative BE_{it} firms are not included in the tests. We do not distinguish among firms by different fiscal year ends.

Various specifications of past stock return are each defined as the arithmetic average of the firm's monthly stock return over some earlier period (holding period returns work equally well for all of our tests):

$$PAST_{i,t}(x,y) = \frac{\sum_{\tau=t-x}^{t-y} Ri,\tau}{y - x + 1} \tag{1}$$

For example, $PAST_{i,t}(1,60)$ is the average monthly return on firm i's common stock over the five years preceding month t; $PAST_{i,t}$ (2,12) is the average monthly return over the last year not including the most recent past month; and $PAST_{i,t}$ (1,1) is the return on the firm's common stock in the month preceding month t.

$PRICE_{it}$ is defined for month t as last month's closing CRSP price for firm i's common stock. $VOLUME_{it}$ is defined as $PRICE_{it}$ times the CRSP reported volume of shares traded for the month preceding month t.

For most of the tests we include all firms that are on the NYSE, AMEX, or NASDAQ exchanges and have the necessary data[3]. Most of our tests take place over the 7/63-12/92 period. The choice of 7/63-12/92 reflects the fact that 1962 is the first year for which we have reliable common equity figures. We also test the robustness of the past return based strategies by examining the earlier 1/27-6/63 period.

III. Tests of Past Return's Power

We test the cross-sectional power of past returns in two ways: (1) We use past returns as right hand side (RHS) variables in Fama-Macbeth (FM) regressions, and (2) We examine some simple portfolios whose construction is based on past returns.

A. Fama-Macbeth Tests

Lo and MacKinlay (1990), Lehmann (1990), and others test the power of past returns to explain future returns. Although appearances differ, their methodology is quite similar to tests which use Fama-Macbeth regressions. Thus, our FM results can be meaningfully compared with the results of other author's tests of the power of past returns[4].

We test three non-overlapping specifications of past returns based on the findings of other authors. The first, PAST(l,l) is last month's common stock return. Many authors [e.g. Jegadeesh (1990), Rosenberg, Reid, and Lanstein (1985)] find that contrarian strategies work when based on monthly returns. The second, PAST(2,12) is last year's average monthly stock return not including last month (so it is averaged over 11 months). Jegadeesh and Titman (1993) find that momentum strategies are effective when defined over a similar time period (although they do not exclude the last month). The third, PAST(13,60), is the average monthly stock return over the last five years, not including last year. DeBondt and Thaler (1985, 1987) argue that long-run contrarian strategies are effective. Our definition of PAST(13,60) is designed to capture this relationship, while not overlapping with our other specifications.

Table 1 presents four separate monthly FM tests run over the 7/63-12/92 period. In each case we report the time-series average and t-statistic of the FM regression coefficients. The coefficients are determined each month from a firm-by-firm cross-sectional regression of realized monthly stock return on the measures of past stock return. If this average is significantly different from zero we have evidence that the past return measure is reliably related to stock returns. If the average is positive, then we have evidence that a continuation (momentum) strategy works. If the average is negative we have evidence that a contrarian strategy works.

Univariately, each past return measure is significant with the sign we expect. PAST(l,l) is strongly negatively priced (t-statistic of -11.59), PAST(2,12) works in a momentum strategy (t-statistic of +3.95), while PAST(l3,60) is significantly contrarian (t-statistic of -4.15). Used together in a multivariate FM test, the results are the same. Based on these FM results, contrarian strategies work based on very short or long-term returns, while momentum based strategies work based on near-term (2-12 month) returns.

B. Quintile Portfolios

Fama-Macbeth tests, while theoretically appealing, may encounter some "real world" difficulties. The portfolios implicitly formed by the FM regressions may contain some extreme and unrealistic positions. Furthermore, the magnitude of the average coefficients can be difficult to interpret. Although the t-tests may be significant, we wish to be assured that the results are "economically significant." We test for this by forming some simple portfolios based on the PAST(x,y) variables.

Before each month we form our universe of stocks into 5 quintile portfolios by sorting only the sample of NYSE firms on one of the PAST(x,y) variables[5]. We determine breakpoints for 5 quintile portfolios from this NYSE sort and then assign each of the

NYSE+AMEX+NASDAQ firms to one of 5 portfolios based on these breakpoints. These portfolios are reformed each month. Table 2 reports the equally weighted average excess return on each quintile portfolio. The far right column contains the average monthly difference between the top (5th) quintile average return and the bottom (1st) quintile average return, and a t-statistic for the test of this difference equaling zero.

These results confirm the findings of the FM regressions, and establish that the power of the PAST(x,y) variables is economically significant. The spread between the top and bottom quintile for each variable is: -1.71% per month for PAST(l,l), + 1.02% per month for PAST(2,12), and -.56% per month for PAST(13,60). The t-statistics for the extreme quintile difference portfolios confirm that these results are statistically reliable, and that our results are not an artifact of portfolio weights implicit in the FM technique. Note, the PAST(l3,60) result is driven by the extreme quintiles (quintile 1 and 5), while the PAST(l,l) and PAST(2,12) variables induce a more monotonic spread.

C. The Importance of Leaving Out the Last Month

Jegadeesh and Titman (1993) find that near-term momentum investing is profitable. However, to be profitable, their portfolios must be held for multiple months. The month after forming portfolios based on near-term momentum, their strategy is unprofitable (their table VII). Put another way, they show that monthly strategies based on contiguous near-term returns are mildly contrarian not momentum in nature. In contrast, we find that monthly strategies based on PAST(2,12) are strongly momentum in nature[6].

Table 3 highlights this difference using two measures of near-term past return both measured contiguous with current returns, PAST(l,12) and PAST(l,6). Clearly, leaving out the last month is vital to the success of the near-term momentum strategy. Using the contiguously measured PAST(l,12) leads to a very weak momentum strategy and PAST(l,6) is actually a contrarian variable[7].

IV. Past Returns vs. Size and Book-to-Market

This section conducts tests of past returns power vs. the size (ME) and book-to-market (BE/ME) variables. We conduct tests over both our full sample of NYSE+AMEX+NASDAQ firms, and over a sample restricted to non-small firms.

A. The Full Sample Tests

Table 4 replicates table 2 (quintile sorts) for ME and BE/ME. We confirm that ME is negatively related to stock returns and that BE/ME is positively related to stock returns. Fama and French (1992) find that these two variables subsume the cross-sectional explanatory power of many other measures.

Table 5 presents the results of sorting on both PAST(1,1) and either ME or BE/ME. At the start of each month we determine NYSE quintile breakpoints for both PAST(l,l) and ME or BE/ME. The intersection of these two quintile sorts gives us 5x5=25 portfolios. Table 5 reports the average equally-weighted monthly excess return on each of the 25 portfolios, the average difference and t-statistic between the high PAST(1,1) and low PAST(1,1) portfolio within each

ME (or BE/ME) quintile, and the average difference and t-statistic between the high ME and low ME portfolio (or between the high BE/ME and low BE/ME portfolio) within each PAST(1,1) quintile. Table 6 replicates table 5 for PAST(2,12), while table 7 does the same for PAST(13,60).

Table 5 shows that the power of PAST(1,1) is far stronger for small firms than for large firms. Among only the smallest firms, there is a -2.56% monthly return spread between high and low PAST(1,1) quintiles, while among only the largest firms there is a -.52% spread. The power of contrarian strategies based on PAST(1,1) may come mostly from the bid-ask spread. If so, we would expect small firms to show a larger PAST(1,1) effect. However, the -.52% spread among only the largest firms is still statistically significant. PAST(1,1) also has great power among firms in any book-to-market quintile. Thus, although bid-ask concerns persist, PAST(1,1) holds up in its first test against the Fama and French variables.

Table 6 tells an even more robust story for PAST(2,12). Like PAST(1,1), PAST(2,12) is more powerful in explaining return differences among small firms. However, as we move to larger firms the return spread induced by sorting on PAST(2,12) drops off proportionately much less than does the spread induced by sorting on PAST(1,1). PAST(2,12) also has power among firms of any book-to-market quintile. The power of PAST(2,12) holds up very well against both Fama and French variables[8].

Table 7 is not kind to PAST(13,60). Although powerful on its own (remember the quintile spreads in table 2), and still negatively related to return among each size quintile, PAST(13,60) only reliably explains returns among the smallest firms. The results for BE/ME x PAST(13,60) sorts are even more striking. PAST(13,60) has explanatory power among the highest BE/ME firms, but nowhere else. Given BE/ME, it seems that PAST(13,60) has little information to add. Although not completely subsumed, the power of PAST(13,60) is greatly reduced when put in competition with the Fama and French variables, especially book-to-market[9].

In table 8 we present the results of a Fama-Macbeth test using all five variables (row 12), and the results of FM tests on subsets of these five variables. In the five variable test we find that each variable is statistically reliable with the sign we would expect from the quintile sorts. All the PAST(x,y) variables remain important when including the Fama and French variables. However, comparing row 8 to row 12, it is clear that PAST(13,60) is somewhat effected by the inclusion of log(ME) and log(BE/ME). In contrast, the PAST(1,1) and PAST(2,12) based strategies are almost totally unaffected by including log(ME) and log(BE/ME) in the FM tests.

B. The Restricted Sample Tests

Our tests in section A. are somewhat contradictory with respect to PAST(13,60). Our two-way quintile sorts show PAST(13,60) has little power for most firms (it only has power for small ME and/or high BE/ME firms). However, even with all other variables included, PAST(13,60) still appears significant in our Fama-Macbeth tests (table 8).

Table 9 carries out additional Fama-Macbeth tests. Panel II. looks at the univariate PAST(13,60) specification and at the five variable specification over only firms whose market capitalization would place it above the first size quintile of NYSE firms (i.e. the biggest 80% of NYSE firms). Due to the presence of AMEX and NASDAQ firms this screen eliminates far more than 20% of our firms. However, on average the screen only removes 3.4% of the total market capitalization of firms.

With no screen (panel I.), PAST(13,60) has a univariate t-statistic of -4.15 and a t-statistic in the multivariate regression of -3.49. Over the restricted sample in panel II., these t-statistics fall to -2.28 and -1.55. In the restricted sample PAST(13,60) has little statistical power beyond our other variables. Taking this restriction further, panel III. eliminates any firm that would fall into the bottom two NYSE size quintiles. This still leaves 91.8% of the market capitalization of our sample in place. Over this restricted sample PAST(13,60) is not significant used alone or vs. the other variables.

It is instructive to look at how our other variables fared over the restricted samples. In panel II. and III. we see that each variable except PAST(13,60) and log(ME) remains significant. Note that the statistical power of PAST(2,12) actually increases in the restricted sample. Aside from firm size itself, only PAST(13,60)'s power seems dependent on the smallest firms.

Now, PAST(13,60)'s failure for all but the smallest firms does not necessarily mean that it is not a true risk factor or profitable anomaly. However, (a) large firms are more focused on by institutions and are the main vehicles for implementable trading strategies, (b) small firms are most affected by illiquidity and trading costs that might swamp any predictability, (c) other biases (e.g. survivorship) are most acute for small firms, and (d) our restricted tests actually only exclude less than 4% and 9% respectively of the total market capitalization[10]. Given these facts, PAST(13,60)'s failure over all but the smallest firms makes us quite skeptical that it represents a variable truly important for the cross-section of expected stock returns.

V. Other Possible Explanations for Past Return's Power

This section examines some possible explanations for the cross-sectional power of our different measures of past return.

A. Beta

Table 10 presents the results of FM regressions that include various combinations of all three past return variables, log(ME), log(BE/ME), and beta. To assign betas to each firm each month the following procedure is used. Each month every firm is assigned to one of 100 portfolios. These 100 portfolios are based on an intersection of 10 decile portfolio formed on last month's firm size, and 10 decile portfolios formed on the firm's individual regression beta vs. the value weighted NYSE+AMEX+NASDAQ portfolio over the last 5 years. Each firm's beta for a given month is the full period beta of the portfolio it is in that month (thus, a firm's beta can change as it moves from portfolio to portfolio)[11].

Replicating results found elsewhere [Fama and French (1992)], we see that when used alone, beta is positively though not significantly priced. However, in competition with our other variables (especially log(ME)), even this weak power disappears.

Table 10 shows that including beta doesn't change any of our conclusions about past return based variables[12].

B. The Bid-Ask Spread, Liquidity, and Short-Term Contrarian Returns

This section examines several hypotheses about the source of PAST(1,1)'s contrarian power. We conduct our own tests, which imply a powerful role for the bid-ask spread, and we examine the work of other authors.

Related hypotheses explaining PAST(1,1)'s power include the effects of the bid-ask spread, liquidity compensation, and the presence of true abnormal contrarian returns. Roll (1984) shows that the bid-ask spread will induce negative serial correlation when returns are measured contiguously. Thus, contrarian strategies based on PAST(1,1) could appear to work based on spreads, while in fact these returns would be unattainable. Under this explanation, contrarian returns would be most pronounced for firms with wide bid-ask spreads. It is also possible that the extra return to PAST(1,1) losers comes from compensation for providing liquidity services [Ho and Stoll (1981), Jegadeesh and Titman (1991)]. If so, contrarian returns should be greater for firms with poor liquidity. Since firms with poor liquidity also tend to have high bid-ask spreads, these hypotheses are related. Also, liquidity may be unconditionally negatively related to expected future return [Amihud and Mendelson (1986)]. This hypothesis implies that expected returns would be positively related to bid-ask spreads. Finally, contrarian PAST(1,l) returns may represent true abnormal returns and thus a market inefficiency [Rosenberg, Reid, and Lanstein (1985)].

We have already tested the three past return variables against firm size (section IV) and found that the power of PAST(l,1) is strongest for small firms. This fits several of the hypotheses outlined above. Small firms often have less liquidity and higher proportional spreads than do large firms. Some other variables that might relate better to liquidity and the bid-ask spread are share price and trading volume (PRICE and VOLUME are defined in section II). Univariate quintile sorts on PRICE induce an average monthly difference between extreme quintiles of -.38% (t-statistic = -1.45) and sorts on VOLUME alone induce an average monthly difference between extreme quintiles of -.56% (t-statistic =-2.44)[13]. Both variables are negatively related to return (as predicted by the liquidity hypothesis), with the volume relation being statistically significant.

Table 11 replicates table 5, using PRICE and VOLUME instead of firm size and book-to-market. Table 11 shows that the power of PAST(l,l) to explain future returns is strongly related to our liquidity measures. The power of PAST(1,1) is rapidly diminishing in both PRICE and VOLUME. This is not surprising given that PRICE and VOLUME are strongly related to ME (we observe a similar effect for ME in table 5). However, the power of PAST(l,1) to explain returns is affected more drastically by sorting into PRICE or VOLUME quintiles than by sorting on ME. For example, among the largest ME firms there is still a significant negative relation between PAST(l ,l) and future returns, among the highest PRICE firms there is an insignificant negative relation between PAST(l,l) and future returns, and among the highest VOLUME firms there is actually a weak positive relation. Note that this last result entails a drastic reversal. The power of PAST(1,1), by far the statistically strongest explanatory variable we study in our initial tests, actually reverses in sign for ex ante high VOLUME firms.

Now, none of the analysis above distinguishes clearly between the liquidity hypotheses, the effect of the bid-ask spread, and true contrarian returns. We attempt to do so now. The unconditional liquidity hypothesis always leads to expected returns being negatively related to liquidity [Amihud and Mendelson (1981)]. The contrarian hypothesis makes no statements about the relation of liquidity and expected future return, while the bid-ask spread hypothesis asserts that the relation between ex ante liquidity and future return will be conditional on past return. We find strong support for the bid-ask spread hypothesis.

Thus far we have discussed the power of PAST(l,1) within PRICE and VOLUME quintiles. However, the power of PRICE and VOLUME within PAST(l,l) quintiles also tells an important story. Consider the lowest PAST(l,l) quintile (column one table 11). Among only these firms, returns are strongly negatively related to both PRICE and VOLUME (quintile spreads of -1.36% per month for PRICE and -1.84% per month for VOLUME). Now consider the highest PAST(l,1) quintile. Returns of these firms are strongly positively related to both PRICE and VOLUME (quintile spreads of +1.25% per month for PRICE and +1.09% per month for VOLUME). Each of these results are strongly statistically significant.

Considering all firms, both PRICE and VOLUME are negative related to future returns (volume is significantly so). However, looking at only firms with ex ante poor performance last month (our lowest PAST(1,1) quintile) leads to a much stronger negative relation between future returns and PRICE and VOLUME (t-statistics of -4.33 and -6.21 respectively). Looking among only firms with ex ante good performance (our highest PAST(l,l) quintile) actually leads to a strong positive relation between ex ante liquidity and future returns Ct-statistics of +4.98 and +4.59 respectively).

The relationship between future return and either PRICE or VOLUME is clearly and strongly conditional on PAST(1,l). This is consistent with the hypothesis that contrarian strategies succeed (or appear to succeed) because of the bid-ask spread. Given that firms have recorded poor performance, it is more likely we have observed a closing price at the bid [Ball, Kothari, and Wasley (1992,1995)]. All else equal, we expect to observe higher performance next month (of course this performance is not achievable, it is bid-ask bounce). This effect is greater the larger the bid-ask spread, and we thus expect to observe better performance for low priced firms and firms with low trading volume. In other words, among poor past performers, we expect PRICE and VOLUME to be negatively related to future return (assuming again that PRICE and VOLUME proxy for liquidity and bid-ask spread). Consider the opposite case. Given that firms have recorded good performance, it is more likely we have observed a closing price at the ask. All else equal, we expect to observe worse performance next month. Furthermore, this effect is greater for firms with higher proportional bid-ask spreads (low PRICE and low VOLUME firms). Thus, among these good past performers, we expect PRICE and VOLUME to be positively related to future returns (higher PRICE or VOLUME implies better liquidity which implies a lower bid-ask spread which means there is a less negative effect from having the prior price recorded at the ask). Importantly, these conditional returns are not driven by PRICE and VOLUME proxying for unconditional compensation for providing liquidity (this relation would always be negative), but by PRICE and VOLUME being related to the bid-ask spread.

In the words of other authors, contrarian strategies can appear effective because of a "bid-ask bounce." By first sorting on PAST(l,l) we determine the direction of the bounce for firms in extreme quintiles (i.e. firms in the lowest PAST(l,l) quintile expect a positive bounce). Then, given the direction of the bounce, variables correlated with the size of the bid-ask spread do an excellent job of forecasting the bounce's magnitude. Considering only the effects of the bid-ask spread, we would predict that (a) future returns should be negatively related to

PAST(l,l), and (b) the relation between future returns and ex ante liquidity should be conditional on PAST(l,l). Both of these predictions fit the evidence perfectly[14].

Other authors have investigated the issue of bid-ask spreads and contrarian strategies with more direct tests. Kaul and Nimalendran (1990) find that the significant returns to daily contrarian strategies go away entirely when the bid-ask spread is explicitly accounted for.

Conrad, Gultekin, and Kaul (1991) examine weekly contrarian strategies and find that for NASDAQ firms all contrarian profits are due to the bid-ask spread. For NYSE+AMEX firms, they find that contrarian profits are still statistically significant after adjusting for bid-ask induced measurement error. However, they find that these bid-ask adjusted profits are of little economic significance. Ball, Kothari, and Wasley (1992) find that after adjusting for bid-ask effects in NASDAQ firm returns, there is no positive return to weekly or monthly contrarian strategies (in fact, they find a weak momentum based return).

In contrast, Jegadeesh (1990) argues that PAST(l,l) contrarian returns are not being driven by the bid-ask spread. He forms PAST(l,1) returns that skip the last trading day of the month. Furthermore, he drops firms that didn't trade on the last day. Thus, his PAST(1,1) skip-a-day returns are guaranteed not to be measured contiguous with future returns. Jegadeesh finds that skip-a-day PAST(1,1) is still quite powerful when used in a contrarian strategy, and thus he concludes that the bid-ask spread is not driving short-term contrarian returns. However, Ball, Kothari, and Wasley (1992) argue that skip-a-day strategies don't necessarily fully account for bid-ask effects. They argue that it doesn't necessarily take only one day to revert to equal probabilities of observing a bid or an ask. Also, they find that bid-ask spreads tend to widen for extreme winners and losers. Thus, if after skipping a day there is still a bid-ask bias, its effects are potentially exacerbated. They argue that their explicit tests on NASDAQ bid-ask data do a better job than does skipping a day of returns for testing bid-ask effects. Although the explicit bid-ask tests seem conclusive, the results of Jegadeesh (1990) still should be reconciled. A detailed study of how bid-ask spreads vary through time is clearly called for. Specifically, defining extreme winners and losers over all but the last day of the month, do these firms have equal probability of trading at the bid or the ask on the actual last day of the month? We leave this question for future research.

We show that the relation between liquidity measures and future return is clearly conditional on past returns. We interpret this as indirect, yet extremely strong, evidence of the importance of bid-ask effects in tests of short-term strategies. Our evidence must be indirect because we wish to examine all of the NYSE+AMEX+NASDAQ firms over our whole period (1963-1992), and extensive bid-ask data is only available for NASDAQ firms post 1982.

Only the bid-ask spread hypothesis jointly fits three empirical observations: (1) The contrarian strategy based on PAST(1,1) appears effective when tested over all firms, (2) The contrarian PAST(1,1) strategy is much less effective (ineffective in the case of high volume firms) among the more liquid firms, and (3) The relation between expected future return and liquidity is strongly conditional on PAST(l,1). We interpret the direct empirical tests of other authors [e.g. Ball, Kothari, and Wasley (1995)] as one source of significant evidence against the overreaction and in favor of the bid-ask hypothesis. We interpret our results detailed above as indirect, yet strong further evidence of the importance of bid-ask spreads for tests of short-term contrarian strategies. Finally, the failure of the short-term contrarian strategy for highly liquid firms (our table 11), and explicit transactions cost adjusted tests from Ball, Kothari, and Wasley, point to extreme difficulties in implementing the short-term contrarian strategy. Together, these results make us quite skeptical that PAST(1,1) truly represents an important source of return predictability.

C. An Earlier Period

One may argue that the breakup of past returns into our 3-variable specification might be spurious and the result of data dredging. While this claim can never be fully refuted, it is instructive to look at how the three variable specification holds in a period we have not yet examined.

We use the period 7/63-12/92 for most of our tests because 1962 is the first year for which we have reliable common equity figures. This is necessary because we wish to compare the results for PAST(x,y) variables with the variables studied by other authors (especially book-to-market). However, when looking at only past return based variables there is no reason to restrict the tests to 7/63-12/92.

Table 12 panel I. presents the results of Fama-Macbeth regressions on PAST(1,1), PAST(2,12), and PAST(l3,60) over the earlier 12/30-6/63 period. Comparing table 12 panel I. with table 1 we see striking similarities. The magnitudes and t-statistics found over 12/30-6/63 are close to those obtained over 7/63-12/92. Most importantly, the sign of each PAST(x,y) variable is the same. Thus, while not eliminating the chance of a spurious specification, the 12/30-6/63 results are exceptionally supportive.

Jegadeesh and Titman (1993) also test their continuation results over earlier periods. They look at 1927-1940 and 1941-1964. They find that the continuation results hold up over

1941-1964, but reverse over 1927-1940 (their table VIII). Once again, we have the opportunity to directly test the effect of our leaving out the last month when forming PAST(2,12). Table 12 panel II. replicates our table 3 for different sample periods. We test PAST(2,12), PAST(1,12), and PAST(1,6) over 1927-1964, 927-1940, and 1941-1964. Like Jegadeesh and Titman, who test related strategies, we find that the momentum strategies using contiguously measured returns, PAST(l,12) and PAST(l,6), are much more successful over 1941-1964 than they are over 1927-1940. In fact, like Jegadeesh and Titman, we find that these strategies actually reverse over 1927-1940 (i.e. contrarian strategies would be better).

Next we look at PAST(2,12). The 1927-1940 result for PAST(2,12) is weaker than it is in other periods. However, unlike the contiguous strategies, the momentum strategy based on PAST(2,12) is still positive over 1927-1940. Jegadeesh and Titman (1993) give a detailed and interesting explanation of why a contiguously measured momentum strategy produces negative returns over 1927-1940. Their explanation involves the continuation strategy's beta and the market's mean reversion. Although this explanation might apply to PAST(2,12)'s reduced strength, it is not needed to explain any pathological results. The PAST(2,12) strategy weakens but does not reverse over 1927-1940.

Finally, PAST(2,12) is significantly positive over the entire earlier period, 1927-1964, while PAST(1,12) and PAST(1,6) are not. Only PAST(2,12) yields a reliable momentum strategy over this earlier period.

Past returns are significant predictors of future returns over both 7/63-12/92 and over earlier periods. Moreover, the earlier period shows the exact same breakup of past returns into those that work in a continuation strategy and those that work in a contrarian strategy. We consider this powerful evidence that (a) our specification is not spurious, and (b) leaving off recent returns is crucial to defining the momentum strategy.

VI. Conclusions

Researchers have discovered numerous past return based strategies that appear powerful for predicting future stock returns. The most important ones are short-term contrarian strategies, near-term momentum strategies, and long-term contrarian strategies. This paper makes several important contributions to this ongoing work. Other research has commonly focused on these strategies one at a time. We test each past return based strategy in a common framework. We define a new 3-variable specification for past returns so as to clearly distinguish the strategies discussed above. We show that this new definition is crucial to our conclusions (i.e. choosing PAST(2,12) vs. PAST(l,12)). We extend our common framework to test past return based strategies against firm size and book-to-market, variables found by other authors to predict stock returns and to subsume the power of many other measures. We test whether other effects may be driving our results (e.g. risk changes, liquidity, bid-ask effects, etc.), and we uncover a new and powerful conditional relation between liquidity and future returns (i.e. that this relation changes based on short-term performance). Finally, we test whether our strong results are period specific.

We find that contrarian strategies based on PAST(l,1) appear successful. However, there is an important caveat. PAST(l ,1) based strategies suffer from measurement problems induced by the bid-ask spread. We find that PAST(l,l)'s efficacy is strongly related to a firm's size and stock price (it works much better for small and/or low priced firms), and even more strongly related to a firm's traded dollar volume (PAST(l,1) does not work at all among ex ante high volume firms). Also, we find that the power of PRICE and VOLUME to explain returns is strikingly dependent on a firm's PAST(1,1). That is, for PAST(1,1) losers, PRICE and VOLUME are strongly negatively related to future returns, while for winners this relationship is strongly positive. These observations, which apply to NYSE+AMEX+NASDAQ firms over our whole sample period, and the more explicit work of other authors on recent NASDAQ returns, all support the argument that bid-ask spreads provide much of the power behind PAST(1,1).

The univariate results for PAST(l3,60) also suffer when examined closely. Though powerful on its own, we show that PAST(l3,60)'s power is very related to ME and log(BE/ME). Most of the power of PAST(l3,60) goes away when log(BE/ME) is held relatively constant (PAST(l3,60) only induces a significant return spread for small firms and for high BE/ME firms). PAST(13,60)'s power seems to be present only for extreme quintiles (in univariate sorts we find quintiles 2-4 to have flat average returns). PAST(l3,60) is still significant in multivariate FM tests[15]. However, when we restrict our attention to all but the smallest firms, but still including over 96% of the market capitalization in our tests, even this significance goes away. Thus, for all of these reasons, we are doubtful that PAST(13,60) is truly necessary to explain stock returns.

We are not at all doubtful about the power of PAST(2,12). The continuation based PAST(2,12) strategy is powerful. This strategy is effective over the 7/63-12/92 test period and over the earlier (e.g. 12/30-6/63) period. Furthermore, the importance of the PAST(2,12) specification vs. specifications measured contiguous with future returns is perfectly robust to testing over earlier periods. This strategy does not seem dependent on small, low priced, or low volume firms[16]. Its measurement is not susceptible to problems induced by the bid-ask spread.

Most important, its power is not attenuated by including size, book-to-market, and/or beta as explanatory variables.

It is interesting to contrast this paper's results for PAST(1,1), PAST(2,12), and PAST(13,60), with the results from other author's tests of past return based strategies. DeBondt and Thaler (1985) focus on long-term contrarian strategies. However, in doing so they ignore their own evidence of the success of one-year based momentum strategies (their table I). Jegadeesh and Titman (1993) uncover new and strong one-year based momentum results. However, their strategy is only successful if portfolios are held for multiple months. Over one-month holding periods, their results still weakly support the success of near-term contrarian strategies (their table VII).

The differences between the results contained in the above two papers and the results of this study highlight the importance of two specification decisions made in this work. First, we skip the last month in forming PAST(2,12). This avoids possible measurement problems. Second, we separate the near-term (one year) from the longer term (2-5 years). This makes sense if either (a) the near-term and long-term truly differ as to whether momentum or contrarian strategies are profitable, or more likely (b) testing a long-term strategy biases us toward validating a contrarian strategy because of the connection between long-term returns and the size and book-to-market variables. Thus, PAST(2,12)'s exclusion of last month and any months before last year is necessary to uncover the strong power of momentum.

In summary, we find that besides size and book-to-market, there is a third variable necessary to explain the cross-section of expected common stock returns[17]. This variable is

PAST(2,12). Explaining the source of PAST(2,12)'s power, a job just begun for size and book-to-market, becomes an important task for the future.

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Table 1

Average Slopes (t-statistics) from Monthly Cross-sectional Regressions of Equity Returns on PAST(l,1), PAST(2,12), and PAST(13,60) NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

PAST(l,1)	PAST(2,12)	PAST(13,60)
-.0610 (-11.59)		
	.0907 (3.95)	
		-.1909 (-4.15)
-.0648 (-13.80)	.0806 (3.54)	-.1880 (-4.28)

PAST(x,y) is the arithmetically averaged monthly past return over the given period (measured relative to the period of the cross-sectional regression). For each month, current returns are cross-sectionally regressed on various combinations of old returns. Each month, a regression coefficient is obtained. Reported here are the time series averages and t-statistics of these regression coefficients.

Each row in the above table represents a separate Fama-Macbeth test. If a row has only one entry it is a univariate test. If a row has multiple entries it represents the results of a multivariate Fama-Macbeth test using the variables from the respective columns.

Table 2
Equally Weighted Average Excess Returns
of Sorted Quintile PAST(x,y) Portfolios
NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

	1	2	3	4	5	5 - 1(t-stat)
PAST(l,1)	1.67	.95	.75	.53	-.04	-1.71 (-9.90)
PAST(2,12)	.32	.62	.74	.92	1.34	1.02 (4.98)
PAST(13,60)	1.10	.80	.77	.76	.54	-.56 (-3.20)

PAST(x,y) is the arithmetically averaged monthly past return over the given period. Before each month we form the stocks into 5 portfolios by first sorting the NYSE firms based on each variable. The NYSE breakpoints are then used to assign the entire universe of NYSE+AMEX+NASDAQ firms to one of five quintile portfolios. We report the equally weighted average excess return on each quintile portfolio. The far right column contains the average difference between the top (5th) quintile return and the bottom (1st) quintile return, and a t-statistic for this difference.

Table 3

Average Slopes (t-statistics) from Monthly Cross-sectional Regressions of Equity Returns on PAST(2,12), PAST(l,12), and PAST(l,6) NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

PAST(2,12)	PAST(l,12)	PAST(l,6)
.0907 (3.95)		
	.0151 (.59)	
		-.0457 (-2.49)

PAST(x,y) is the arithmetically averaged monthly past return over the given period (measured relative to the period of the cross-sectional regression). For each month, current returns are cross-sectionally regressed on various combinations of old returns. Each month, a regression coefficient is obtained. Reported here are the time series averages and t-statistics of these regression coefficients.

Each row in the above table represents a separate Fama-Macbeth test. If a row has only one entry it is a univariate test. If a row has multiple entries it represents the results of a multivariate Fama-Macbeth test using the variables from the respective columns.

Table 4
Equally Weighted Average Excess Returns on
Sorted Quintile ME and BE/ME Portfolios
NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

	1	2	3	4	5	5 - 1 (t-stat)
ME	1.06	.83	.64	.56	.37	-.69 (-2.62)
BE/ME	.37	.56	.77	.99	1.28	.91 (5.01)

ME is the market value of common equity as defined in section 1. BE/ME is the ratio of book value of common equity to market value of common equity as defined in section 1. Before each month we form the stocks into 5 portfolios by first sorting the NYSE firms based on each variable. The NYSE breakpoints are then used to assign the entire universe of NYSE+AMEX+NASDAQ firms to one of five quintile portfolios. We report the equally weighted average excess return on each quintile portfolio. The far right column contains the average difference between the top (5th) quintile return and the bottom (1st) quintile return, and a t-statistic for this difference.

Table 5

Equally Weighted Excess Returns on 5x5 Quintile Portfolios
Formed on PAST(1,1) and either ME or BE/ME
NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

ME x PAST(l,l)

	Quintile 1 PAST(1,1)	Quintile 2 PAST(1,1)	Quintile 3 PAST(1,1)	Quintile 4 PAST(1,1)	Quintile 5 PAST(1,1)	Diff. (t-stat)
Quintile 1 ME	2.18	1.35	1.06	.67	-.38	-2.56 (-14.42)
Quintile 2 ME	1.43	1.05	.77	.60	.34	-1.10 (-6.52)
Quintile 3 ME	1.14	.81	.74	.47	.19	-.95 (-5.21)
Quintile 4 ME	1.07	.77	.57	.41	.20	-.86 (-4.56)
Quintile 5 ME	.70	.45	.34	.32	.18	-.52 (-2.58)
Diff. (t-stat)	-1.48 (-4.61)	-.90 (-3.57)	-.72 (-2.86)	-.35 (-1.42)	.56 (2.25)	

BE/ME x PAST(1,1)

	Quintile 1 PAST(1,1)	Quintile 2 PAST(1,1)	Quintile 3 PAST(1,1)	Quintile 4 PAST(1,1)	Quintile 5 PAST(1,1)	Diff. (t-stat)
Quintile 1 BE/ME	1.08	.51	.33	.12	-.34	-1.42 (-7.83)
Quintile 2 BE/ME	1.35	.77	.50	.33	-.14	-1.49 (-7.97)
Quintile 3 BE/ME	1.66	.92	.68	.52	.01	-1.65 (-8.20)
Quintile 4 BE/ME	1.92	1.14	.93	.66	.11	-1.81 (-9.12)
Quintile 5 BE/ME	2.42	1.51	1.32	.90	.06	-2.36 (-11.98)
Diff. (t-stat)	1.34 (5.99)	1.00 (5.26)	.99 (5.08)	.78 (3.90)	.40 (2.13)	

PAST(l,l) is the arithmetically averaged monthly past return over the given period. ME is the market value of common equity as defined in section 1. BE/ME is the ratio of book value of common equity to market value of common equity as defined in section 1. Before each month we sort only the NYSE firms into quintiles based on three variables: PAST(l,l), ME, and BE/ME. We then take the 5x5 intersection of these quintile portfolios to determine breakpoints for 25 portfolios. We then assign each of the NYSE+AMEX+NASDAQ firms to one of these 25 portfolios each month. We report the equally weighted average monthly return on each of these 25 portfolios from the 5x5 ME vs. PAST(l,l) sort, and from the 5x5 BE/ME vs. PAST(l,l) sort. The far right column contains the average and t-statistic for the difference between the high column quintile return and the low column quintile return within a given row. The bottom row contains the corresponding statistics for the row differences within each column.

Table 6

Equally Weighted Excess Returns on 5x5 Quintile Portfolios

Formed on PAST(2,12) and either ME or BE/ME

NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

ME x PAST(2,l2)

	Quintile 1 PAST(2,12)	Quintile 2 PAST(2,12)	Quintile 3 PAST(2,12)	Quintile 4 PAST(2,12)	Quintile 5 PAST(2,12)	Diff. (t-stat)
Quintile 1 ME	.49	1.00	1.17	1.31	1.52	1.03 (5.47)
Quintile 2 ME	.27	.56	.78	1.02	1.27	1.00 (4.69)
Quintile 3 ME	.17	.41	.56	.67	1.21	1.04 (4.62)
Quintile 4 ME	.32	.41	.43	.59	1.03	.71 (2.93)
Quintile 5 ME	.16	.34	.24	.44	.74	.58 (2.31)
Diff. (t-stat)	-.33 (-.94)	-.66 (-2.62)	-.93 (-3.99)	-.87 (-3.49)	-.78 (-2.91)	

BE/ME x PAST(2,l2)

	Quintile 1 PAST(2,12)	Quintile 2 PAST(2,12)	Quintile 3 PAST(2,12)	Quintile 4 PAST(2,12)	Quintile 5 PAST(2,12)	Diff. (t-stat)
Quintile 1 BE/ME	-.32	.10	.30	.52	1.13	1.45 (6.15)
Quintile 2 BE/ME	.14	.43	.40	.62	1.17	1.03 (4.45)
Quintile 3 BE/ME	.50	.61	.65	.78	1.23	.73 (2.91)
Quintile 4 BE/ME	.60	.83	.95	.98	1.48	.88 (3.81)
Quintile 5 BE/ME	.90	1.12	1.29	1.52	1.57	.67 (3.01)
Diff. (t-stat)	1.22 (5.37)	1.02 (4.57)	.99 (5.02)	1.00 (4.83)	.44 (2.24)	

PAST(2,12) is the arithmetically averaged monthly past return over the given period. ME is the market value of common equity as defined in section 1. BE/ME is the ratio of book value of common equity to market value of common equity as defined in section 1. Before each month we sort only the NYSE firms into quintiles based on three variables: PAST(2,12), ME, and BE/ME. We then take the 5x5 intersection of these quintile portfolios to determine breakpoints for 25 portfolios. We then assign each of the NYSE+AMEX+NASDAQ firms to one of these 25 portfolios each month. We report the equally weighted average monthly return on each of these 25 portfolios from the 5x5 ME vs. PAST(2,12) sort, and from the 5x5 BE/ME vs. PAST(2,12) sort. The far right column contains the average and t-statistic for the difference between the high column quintile return and the low column quintile return within a given row. The bottom row contains the corresponding statistics for the row differences within each column.

Table 7
Equally Weighted Excess Returns on 5x5 Quintile Portfolios
Formed on PAST(13,60) and either ME or BE/ME
NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

ME x PAST(13,60)

	Quintile 1 PAST(13,60)	Quintile 2 PAST(13,60)	Quintile 3 PAST(13,60)	Quintile 4 PAST(13,60)	Quintile 5 PAST(13,60)	Diff. (t-stat)
Quintile 1 ME	1.32	1.12	1.03	.95	.63	-.68 (-4.67)
Quintile 2 ME	.94	.84	.87	.84	.68	-.26 (-1.61)
Quintile 3 ME	.75	.62	.71	.67	.57	-.18 (-1.08)
Quintile 4 ME	.80	.55	.57	.65	.43	-.37 (-1.94)
Quintile 5 ME	.41	.49	.47	.42	.24	-.17 (-.89)
Diff. (t-stat)	-.91 (-2.90)	-.63 (-2.70)	-.56 (-2.33)	-.53 (-2.25)	-.39 (.1.52)	

BE/ME x PAST(13,60)

	Quintile 1 PAST(13,60)	Quintile 2 PAST(13,60)	Quintile 3 PAST(13,60)	Quintile 4 PAST(13,60)	Quintile 5 PAST(13,60)	Diff. (t-stat)
Quintile 1 BE/ME	.55	.54	.50	.52	.31	-.24 (-1.08)
Quintile 2 BE/ME	.72	.55	.55	.64	.54	-.18 (-.94)
Quintile 3 BE/ME	.88	.64	.72	.78	.78	-.10 (-.62)
Quintile 4 BE/ME	1.06	.93	.96	.96	.92	-.14 (-.87)
Quintile 5 BE/ME	1.44	1.13	1.09	1.03	.99	-.45 (-2.46)
Diff. (t-stat)	.89 (4.84)	.59 (3.21)	.59 (3.46)	.51 (2.68)	.68 (4.02)	

PAST(13,60) is the arithmetically averaged monthly past return over the given period. ME is the market value of common equity as defined in section 1. BE/ME is the ratio of book value of common equity to market value of common equity as defined section 1. Before each month we sort only the NYSE firms into quintiles based on three variables: PAST(13,60), ME, and BE/ME. We then take the 5x5 intersection of these quintile portfolios to determine breakpoints for 25 portfolios. We then assign each of the NYSE+AMEX+NASDAQ firms to one of these 25 portfolios each month. We report the equally weighted average monthly return on each of these 25 portfolios from the 5x5 ME vs. PAST(13,60) sort, and from the 5x5 BE/ME vs. PAST(13,60) sort. The far right column contains the average and t-statistic for the difference between the high column quintile return and the low column quintile return within a given row. The bottom row contains the corresponding statistics for the row differences within each column.

Table 8
Average Slopes (t-statistics) from Monthly Cross-sectional Regressions of Equity Returns on PAST(1,1), PAST(2,12), PAST(l3,60), Log(ME), and Log(BE/ME)
NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

Test	PAST(1,1)	PAST(2,12)	PAST(l3,60)	log(ME)	log(BE/ME)
(1)			-.1909 (-4.15)		
(2)				-.1888 (-3.35)	
(3)					.4098 (6.06)
(4)				-.1708 (-2.98)	.2599 (4.11)
(5)			-.1414 (-4.24)	-.1634 (-3.10)	
(6)			-.1389 (-3.18)		.3227 (5.59)
(7)			-.1059 (-3.31)	-.1587 (-2.58)	.2021 (3.39)
(8)	-.0648 (-13.80)	.0806 (3.54)	-.1880 (-4.28)		
(9)	-.0690 (-15.66)	.0801 (3.79)		-.1293 (-2.58)	.3364 (4.81)
(10)	-.0687 (-15.63)	.0765 (3.72)	-.1489 (-4.39)	-.1429 (-2.97)	
(11)	-.0667 (-14.25)	.0754 (3.31)	-.1275 (-3.19)		.3573 (6.31)
(12)	-.0708 (-16.17)	.0710 (3.51)	-.1125 (-3.49)	-.1308 (-2.64)	.2418 (4.35)

PAST(x,y) is the arithmetically averaged monthly past return over the given period. ME is the market value of common equity as defined in section 1. BE/ME is the ratio of book value of common equity to market value of common equity as defined in section 1. For each month, current returns are cross-sectionally regressed on various combinations of explanatory variables. Each month, a regression coefficient is obtained. Reported here are the time series averages and t-statistics of these regression coefficients. Each row in the above table represents a separate Fama-Macbeth test. If a row has only one entry it is a univariate test. If a row has multiple entries it represents the results of a multivariate Fama-Macbeth test using the variables from the respective columns.

Table 9
Average Slopes (t-statistics) from Monthly Cross-sectional Regressions of Equity Returns on PAST(l,1), PAST(2,12), PAST(13,60), Log(ME), and Log(BE/ME) Done for All Firms and for Non-Small Firms NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

Panel I. All Firms Included

PAST(1,1)	PAST(2,12)	PAST(13,60)	log(ME)	log(BE/ME)
		-.1909 (-4.15)		
-.0708 (-16.17)	.0710 (3.51)	-.1125 (-3.49)	-.1308 (-2.64)	.2418 (4.35)

Panel II. No firms with market capitalization in bottom quintile of NYSE market capitalizations

PAST(1,1)	PAST(2,12)	PAST(13,60)	log(ME)	log(BE/ME)
		-.0963 (-2.28)		
-.0416 (-8.20)	.1433 (5.50)	-.0479 (-1.55)	-.0681 (-1.66)	.2201 (3.57)

Panel III. No firms with market capitalization in bottom two quintiles of NYSE market capitalizations

PAST(1,1)	PAST(2,12)	PAST(13,60)	log(ME)	log(BE/ME)
		-.0859 (-1.86)		
-.0434 (-7.68)	.1478 (5.06)	-.0394 (-1.11)	-.0701 (-1.70)	.1893 (2.83)

PAST{x,y) is the arithmetically averaged monthly past return over the given period. ME is the market value of common equity as defined in section 1. BE/ME is the ratio of book value of common equity to market value of common equity as defined in section 1. Beta for each firm is the full period summed beta of the portfolio of 100 ME x regression pre-beta portfolios formed each month (see section IV. A. for a description of this methodology). For each month, current returns are cross-sectionally regressed on various combinations of explanatory variables. Each month, a regression coefficient is obtained. Reported here are the time series averages and t-statistics of these regression coefficients. Each row in the above table represents a separate Fama-Macbeth test. If a row has only one entry it is a univariate test. If a row has multiple entries it represents the results of a multivariate Fama-Macbeth test using the variables from the respective columns.

These tests are done including various subsets of firms. First, in panel 1we repeat the tests using all firms. Panel II. excludes any firm whose market capitalization would place it in the bottom size quintile of NYSE firms. Panel III. excludes any firm whose market capitalization would place it in the bottom two size quintiles of NYSE firms.

Excluding firms that wouldn't be in the bottom size quintile of NYSE firms results in the average number of firms in our sample dropping from 3166 per month in panel I, to 1233 in panel II (for the five variable case). However, on average the sample in panel II. had 96.6% of the total market capitalization of the sample in panel I.

Excluding firms that wouldn't be in the bottom two size quintiles of NYSE firms results in the average number of firms in our sample dropping from 3166 per month in panel I., to 754 in panel III (for the five variable case). However, on average the sample in panel III. had 91.80% of the total market capitalization of the sample in panel I.

Table 10

Average Slopes (t-statistics) from Monthly Cross-sectional Regressions of Equity Returns on PAST(l,1), PAST(2,12), PAST(l3,60), Log(ME), Log(BE/ME), and Beta

NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

Test	PAST(1,1)	PAST(2,12)	PAST(13,60)	log(ME)	log(BE/ME)	Beta
(I)	-.0648 (-13.80)	.0806 (3.54)	-.1880 (-4.28)			
(2)	-.0708 (-16.17)	.0710 (3.51)	-.1125 (-3.49)	-.1308 (-2.64)	-.2418 (4.35)	
(3)						.3218 (1.21)
(4)				-.2032 (-.3.88)		-.1265 (-.56)
(5)					.3878 (6.05)	.3186 (1.23)
(6)				-.1798 (-3.41)	.2543 (4.24)	-.0493 (-.23)
(7)	-.0716 (-15.64)	.0741 (3.62)	-.1938 (-4.68)			.3574 (1.41)
(8)	-.0718 (-16.49)	.0781 (4.01)	-.1498 (-4.59)	-.1477 (-3.26)		.0198 (.09)
(9)	-.0733 (-16.08)	.0702 (3.44)	-.1346 (-3.50)		.3433 (6.10)	.3272 (1.29)
(10)	-.0737 (-16.97)	.0733 (3.80)	-.1101 (-3.49)	-.1318 (-2.86)	.2540 (4.52)	.0449 (.20)

PAST(x,y) is the arithmetically averaged monthly past return over the given period. ME is the market value of common equity as defined in section 1. BE/ME is the ratio of book value of common equity to market value of common equity as defined in section 1. Beta for each firm is the full period summed beta of the portfolio of 100 ME x regression pre-beta portfolios formed each month (see section IV. A. for a description of this methodology). For each month, current returns are cross-sectionally regressed on various combinations of explanatory variables. Each month, a regression coefficient is obtained. Reported here are the time series averages and t-statistics of these regression coefficients. Each row in the above table represents a separate Fama-Macbeth test. If a row has only one entry it is a univariate test. If a row has multiple entries it represents the results of a multivariate Fama-Macbeth test using the variables from the respective columns.

Table 11

Equally Weighted Excess Returns on 5x5 Quintile Portfolios
Formed on PAST(l,l) and either PRICE or VOLUME
NYSE+AMEX+NASDAQ Firms (7/63 - 12/92)

PRICE x PAST(1,1)

	Quintile 1 PAST(1,1)	Quintile 2 PAST(1,1)	Quintile 3 PAST(1,1)	Quintile 4 PAST(1,1)	Quintile 5 PAST(1,1)	Diff. (t-stat)
Quintile 1 PRICE	2.18	1.21	.92	.56	-.66	-2.84 (-16.48)
Quintile 2 PRICE	1.33	1.05	.82	.53	.27	-1.05 (-6.51)
Quintile 3 PRICE	1.28	1.05	.82	.53	.27	-1.05 (-6.30)
Quintile 4 PRICE	1.11	.79	.61	.50	.28	.83 (-5.19)
Quintile 5 PRICE	.82	.65	.56	.46	.59	-.23 (-1.23)
Diff. (t-stat)	-1.36 (-4.33)	-.56 (-2.16)	-.36 (-1.39)	-.10 (-.42)	1.25 (4.98)	

VOLUME x PAST(1,1)

	Quintile 1 PAST(1,1)	Quintile 2 PAST(1,1)	Quintile 3 PAST(1,1)	Quintile 4 PAST(1,1)	Quintile 5 PAST(1,1)	Diff. (t-stat)
Quintile 1 VOLUME	2.22	1.18	.96	.60	-.53	-2.75 (-15.98)
Quintile 2 VOLUME	1.43	.91	.74	.48	.04	-1.38 (-7.67)
Quintile 3 VOLUME	1.08	.80	.66	.55	.15	.93 (-5.28)
Quintile 4 VOLUME	.98	.80	.59	.50	.38	-.60 (-3.08)
Quintile 5 VOLUME	.38	.53	.49	.52	.56	.18 (.80)
Diff. (t-stat)	-1.84 (-6.21)	-.65 (-2.93)	-.47 (-2.93)	-.08 (-.35)	1.09 (4.59)	

PAST(l,l) is the arithmetically averaged monthly past return over the given period. PRICE is the CRSP reported price for the prior month's end. VOLUME is the CRSP reported trading volume in shares for the prior month times PRICE. Before each month we sort only the NYSE firms into quintiles based on three variables: PAST(l,l), PRICE, and VOLUME. We then take the 5x5 intersection of these quintile portfolios to determine breakpoints for 25 portfolios. We then assign each of the NYSE+AMEX+NASDAQ firms to one of these 25 portfolios each month. We report the equally weighted average monthly return on each of these 25 portfolios from the 5x5 PRICE vs. PAST(1,1) sort, and from the 5x5 VOLUME vs. PAST(1,1) sort. The far right column contains the average and t-statistic for the difference between the high column quintile return and the low column quintile return within a given row. The bottom row contains the corresponding statistics for the row differences within each column.

Table 12

Average Slopes (t-statistics) from Monthly Cross-sectional Regressions of Equity Returns on Various PAST(x,y) NYSE+AMEX Firms (1/27-12/64)

Panel l

TimePeriod	PAST(1,1)	PAST(2,12)	PAST(13,60)
12/30-6/63	-.1014 (-11.53)		
		.1123 (3.25)	
			-.1305 (-2.08)
	-.1059 (-12.81)	.1104 (3.39)	-.1427 (-2.39)

Panel II

Time Period	PAST(2,12)	PAST(2,12)	PAST(2,12)
1/27-12/40	.0438 (.71)		
		-.1294 (-1.89)	
			-.2171 (-4.05)
1/41-12/64	.1626 (5.05)		
		.0827 (2.29)	
			.0044 (.1843)
l/27-12164	.1188 (3.90)		
		.0046 (.13)	
			-.0772 (-3.06)

PAST(x,y) is the arithmetically averaged monthly past return over the given period (measured relative to the period of the cross-sectional regression). For each month, current returns are cross-sectionally regressed on various combinations of old returns. Each month, a regression coefficient is obtained. Reported here are the time series averages and t-statistics of these regression coefficients.

Each row in the above table represents a separate Fama-Macbeth test. If a row has only one entry it is a univariate test. If a row has multiple entries it represents the results of a multivariate Fama-Macbeth test using the variables from the respective columns.

FOOTNOTES

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[1] Roll (1984) shows that the bid-ask spread can induce negative serial correlation in stock returns.

[2] Throughout this paper we say a variable "explains" stock returns if we have evidence that the variable is unconditionally priced.

[3] This paper's conclusions don't change if NASDAQ firms are excluded. These results are available from the author.

[4] An appendix detailing this similarity is available from the author on request.

[5] We calculate all sort breakpoints in this paper using only the sample of NYSE firms (no AMEX or NASDAQ). This keeps our market value sorts from putting mostly NYSE (NASDAQ) firms in the top (bottom) quintiles. The results for sorts on past return are not significantly effected by this choice.

[6] Our results also hold up quite well for portfolios held for up to one year (tables available on request).

[7] Jegadeesh and Titman (1993) do look at strategies that skip a week between return measurement and portfolio construction, although they do not focus on these results. They also find that non-contiguous measurement improves momentum strategies. However, their one- week adjustments have a much smaller impact than the impact we find comparing PAST(2,12) results to PAST(l,12) and PAST(l,6).

[8] Interestingly, the size effect seems quite weak among PAST(2,12) losers (column one top panel). We leave this observation for future study.

[9] We don't explicitly test the strategies studied by DeBondt and Thaler (1985, 1987). However, the results of this section imply that the success of their long term contrarian strategy could well be, at least partly, a manifestation of the book-to-market and size effects.

[10] Lakonishok, Vishny, and Shleifer (1994) raise similar points and conduct similar tests of their variables power over only large firms.

[11] Fama and French (1992) use a very similar method to assign betas.

[12] Additional tests for "performance induced shifts in beta" were also carried out. For instance, the full period betas of quintile portfolios formed each month on PAST(x,y)s were examined. In no case was changing beta found to have any significant power to explain the returns to past return based strategies.

[13] These tables are available on request.

[14] We have conducted two additional robustness tests of these results. One, the relation between volume and contrarian returns for only NYSE firms is economically and statistically quite similar to the relation among firms on all three exchanges. Two, using an extra month lag to determine volume (so it is not measured contemporaneously with PAST(l,l)) has no appreciable effect on the results.

[15] Fama and French (1994) test a version of PAST(l3,60) against their three factor model. They find that when sorted by PAST(l3,60), decile portfolios do not have significant intercepts in time-series regressions against their other three factors. These time-series tests are related to, yet distinct from our cross-sectional work (see their paper for a discussion of this relation).

[16] The price and volume vs. PAST(2,12) sorts are available on request.

[17] Fama and French (1993) find they must add a different third factor to size and book-to-market. They must add the market return. This is because they are attempting to explain time-series

regression intercepts and the market return is necessary to explain the difference between stock returns and t-bills. In the context of their time-series model, we would argue we have found a fourth factor.

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