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Paper Number 07/13

Revised Version July 2007

Forthcoming: *Journal of Financial and Quantitative Analysis*, 2008

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Abstract

It has been hypothesized that momentum might be rationally explained as a consequence of the cross-sectional variation of unconditional expected returns. Stocks with relatively high unconditional expected returns will on average outperform in both the portfolio formation period and in the subsequent holding period. We evaluate this explanation by first removing unconditional expected returns for each stock from raw returns and then test for momentum in the resulting series. We measure the unconditional expected return on each stock as its mean return in the whole sample period. We find momentum effects vanish in demeaned returns.

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I. Introduction

Evidence that portfolios of stocks that have recently performed relatively well go on to deliver higher returns in the near future than those that have recently performed relatively badly was reported by Jegadeesh and Titman (1993). Subsequent work has confirmed the robustness of this result. Similar findings are reported both in samples of data observed after the result was first documented, Jegadeesh and Titman (2001), Korajczyk and Sadka (2004), and in data from different countries, Rouwenhorst (1998).

This evidence is widely interpreted as evidence of time-varying returns for individual stocks and the problem is then to explain, in the context of a conventional model of asset-pricing, why time variation in expected returns might exhibit momentum. Fama (1998) has described this apparent anomaly as one of the most difficult to explain in a model of rational asset-pricing and understanding this result has become an important challenge. Theoretical models that have subsequently been proposed to explain time-varying expected returns that are consistent with evidence of momentum include Berk, Green, and Naik (1999) and Johnson (2002).

Empirical work has investigated whether these results might be rationally explained by positive serial correlation in factor returns so that momentum strategies will pick stocks with high loadings on factor portfolios that have a relatively high conditional expected return. However Fama and French (1996) and Grundy and Martin (2001) find that momentum effects persist after controlling for time variation in returns using the Fama and French three-factor model. A notable success is that of Chordia and Shivakumar (2002) who do successfully identify a small set of macro factors that can explain momentum. If there is an explanation for momentum based on macro factors one would expect to see this show up in industry returns and several authors have investigated whether momentum of individual stocks simply reflects industry momentum. Moskowitz and Grinblatt (1999) report evidence that industry effects can largely explain the evidence although in subsequent work Grundy and Martin (2001), Chordia and Shivakumar (2002), Lewellen (2002) and Ahn, Conrad, and Dittmar (2003) all find that stock momentum cannot be fully accounted for by industry momentum.

A different perspective on momentum is that it does not reflect time-varying returns but simply cross-sectional differences in unconditional expected returns between stocks, where expected returns might for example be determined by the capital asset pricing model of Sharpe (1964) and Lintner (1965). Stocks with relatively high unconditional expected returns will outperform in both portfolio formation periods and subsequent holding periods. This point is noted by Lo and MacKinlay (1990), Jegadeesh and Titman (1993), and developed further by Conrad and Kaul (1998). Jegadeesh and Titman (1993) investigate the hypothesis that momentum profits could be explained by the cross-sectional dispersion of unconditional expected returns, but they rejected this explanation, using size and beta as a measure of expected returns.

In this paper we take a different approach to testing whether momentum can be explained by the cross-sectional dispersion in expected returns. In the absence of any consensus about the correct model for expected returns we measure the unconditional expected return for each stock as the average return on that stock over the full sample period. We then remove this estimate of expected returns from raw returns and apply the conventional tests for momentum to the resulting series of demeaned returns, our empirical measure of (unconditionally) unexpected returns. In Section II we describe our approach in more detail, in Section III we describe our data and methodology, in Section IV we report results, and Section V concludes.

II. Testing the Hypothesis that the Cross-Sectional Variation in Expected Returns Explains Momentum

The problem in testing whether the cross-sectional variation in unconditional expected returns can explain momentum using any specific model of expected returns is that if there is any model error, then the resulting residual dispersion in expected returns that are not captured by the model will show up as momentum. Jegadeesh and Titman (2001) note this problem and adopt an approach that does not require specification of a model of expected returns. Their test specifically serves to evaluate the model of Conrad and Kaul (1998) who assume that expected returns are rationally determined, different across stocks, and time invariant. This model implies that returns for holding periods of any length should be positively correlated with returns in the portfolio formation periods. Jegadeesh and Titman (2001) report that on the contrary, when the portfolio holding period is increased beyond twelve months, then past winners start to become losers, and hence infer that returns are time-varying and so reject the model of Conrad and Kaul as an explanation for momentum.

The methodology of Jegadeesh and Titman (2001) does establish that there is a time-varying component to returns, since returns on "winner" portfolios, which were initially positive, became negative as holding periods are increased beyond one year. Return reversals clearly cannot be explained away by the cross-sectional dispersion of expected returns. However it does not directly address the source of the momentum profits in the short term. For example the results of Jegadeesh and Titman (2001) are consistent with the hypothesis that the cross-sectional dispersion in expected returns explains the profits to momentum strategies at horizons of under a year and that the only time-varying component to returns takes the form of reversals, which overwhelm the effect of the dispersion in unconditional expected returns at longer horizons.

In this paper we focus on the question of whether there is also, at shorter horizons, a momentum component to time-varying returns, in addition to the reversals at longer horizons identified by Jegadeesh and Titman (2001). We apply the idea, introduced by Lo and MacKinlay (1990), and emphasised by Conrad and Kaul (1998), that the success of returns based trading strategies should be decomposed into a component due to the cross-sectional dispersion in unconditional expected returns and a component due to time-series variation in stock returns. In the absence of any consensus about the correct model of expected returns we take an empirical approach and measure the unconditional expected return on each stock as the mean return for that stock measured over the full sample period[1]. We then remove the component of stock returns due to the cross-sectional dispersion of expected returns by subtracting

[1] We actually use a two-step procedure to demean which we describe in Section 2. For ease of exposition we simply describe our method as demeaning, which captures the spirit of our methodology.

the sample mean return for each stock from its raw return at each date and test for evidence of momentum in the resulting series of demeaned returns[2].

The objective here is not to test a new trading strategy but to better understand why a conventional momentum strategy is successful. If we were to find evidence of momentum in demeaned returns this would not imply that a profitable trading rule to exploit this time variation could have been employed in practice. An investor trading in real time cannot purchase portfolios on the basis of returns that are adjusted at each date using a sample mean constructed from data that are not yet available. However a *necessary* condition for such a strategy being profitable is that there is a significant time-varying component to returns, superimposed on the cross-sectional dispersion in unconditional returns. If we were to find momentum in demeaned returns then this would beg the further interesting question of whether investors, trading in calendar time and estimating mean stock returns from only past data, could profit by a momentum trading strategy. However since we find that a momentum trading strategy would not even be profitable to a trader who had the advantage of measuring unconditional expected returns by full sample means, this further question does not arise.

[2] Lo and MacKinlay (1990) also note that the time-varying component of returns to trading strategies can be further decomposed into that due to the autocorrelation in individual security returns and that due cross-autocorrelations between securities. However they report evidence for cross-effects only at weekly horizons, which they explain by non-synchronous trading and bid-ask spreads. Since we find no evidence of momentum in demeaned returns, at the longer horizons that we study, we do not pursue this further decomposition.

We start by confirming that momentum effects are still present in raw returns in a data set extended to 1965–2005, using a similar methodology to that of Jegadeesh and Titman (1993). We then apply the same tests to the series of demeaned returns. We find no evidence for momentum in demeaned returns. We also test two further implications of this explanation for momentum. If portfolios are formed on the basis of raw returns we should expect to find that stocks with relatively high mean returns, measured over the full sample, are on average over-represented in "winner" portfolios and under-represented in "loser" portfolios (and conversely for low mean return stocks). Secondly, if the reason that portfolios of "winners" perform relatively well is that they are over-weight in high unconditional expected returns stocks, then portfolios that are constructed on the basis of high sample means should perform even better, since recent returns are a relatively noisier measure of unconditional expected returns. On the other hand if the reason that "winners" outperform is that these portfolios exploit momentum, then discarding information on recent returns should lead to lower subsequent returns[3]. We find that winner-loser portfolios are relatively over weight in stocks with high unconditional expected returns and that returns to portfolios formed on full sample means are greater than to those formed on recent momentum. In Section II we describe our data and methodology, in Section III we report results, and Section IV concludes.

III. Measurement of Expected Returns and Construction of Tests

The objective is to capture the dispersion of unconditional expected returns in a way that is not contingent on any specific model of asset pricing. Our approach is to measure the unconditional expected returns on a stock by the average of the realized

[3] We thank the referee for suggesting both of these corollaries.

returns on that stock in the full sample. However in order to implement this idea we first remove the market return at each date and calculate the mean difference between the return on each stock and the market. The reason for this two step procedure is that many stocks are listed only for sub-periods and there is substantial time variation in aggregate stock returns, even measured over horizons of several years. Simply measuring a stock's unconditional expected return by its average return would mean that the estimate of an individual stock's expected return would inherit the properties of the market return during its listing. This would introduce a significant bias into the estimates of expected returns, the size and direction of which would depend on the performance of the market during the listing of the different stocks. For example suppose the cross-sectional dispersion in expected returns is explained by the Capital Asset Pricing Model. Consider two stocks with the same Beta, but suppose also that one stock has only been listed for the last five years, which happened to be a period of high returns to the whole market, but the other has been listed for a longer period, spanning both bull and bear markets. Then the mean return calculated directly from raw returns would typically be higher for the stock that was only listed during the bull phase. Our two-stage procedure eliminates this bias.

This two-step procedure is summarized as follows. For any month *t*, we subtract the return on a market portfolio, $R_{m,t}$, from each stock's return, $R_{i,t}$, to give a market-adjusted return, $\hat{R}_{i,t} = R_{i,t} - R_{m,t}$. $\hat{R}_{i,t}$ is further decomposed into an unconditional firm specific expected return, $E(\hat{R}_i)$, and the deviation from this, $\hat{\hat{R}}_{i,t}$, giving:

$$\hat{\hat{R}}_{i,t} = \hat{R}_{i,t} - E(\hat{R}_i).$$

$\hat{\hat{R}}_{i,t}$ is our measure of the demeaned return on stock *i* at date *t*. It is the difference between the deviation from the market of raw returns on stock *i* at date *t* and the average deviation of raw returns on stock *i* from the market. $E(\hat{R}_{i,t})$ is empirically calculated as:

$$E(\hat{R}_i) = \frac{1}{S}\sum_{t=1}^{S}(R_{i,t} - R_{m,t}),$$

where *S* is the total number of time-series observations available for a particular stock *i* available in our sample period. We then rank stocks and record subsequent performance using the series of demeaned returns, $\hat{\hat{R}}_{i,t}$. This methodology cannot be expected to give reliable results for stocks that are only listed for short periods and therefore we exclude from the sample stocks that are listed for less than twenty-four months.

We evaluate the profitability of momentum strategies in both raw returns and demeaned returns as follows. In a month *t*, stocks are ranked in ascending order according to their previous *J*-month cumulated returns. The top decile of the sorted stocks is labeled the 'winner' portfolio and the bottom decile the 'loser' portfolio. *K*-month average cumulated equally-weighted returns, rebalancing every month, are computed for the respective portfolios. We consider strategies for all combinations of *J* and *K* equal to 3, 6, 9 and 12 months. Holding period returns are calculated starting at the same date *t* that stocks are ranked and portfolios formed[4]. Repeating this

[4] Some authors skip a week or a month before starting to calculate holding period returns so when comparing results with others reported in the literature the fact that we do not skip any time before computing holding period returns may lengthen the initial period over which negative returns are

strategy each successive month would induce the interrelated problems of overlapping returns and overlapping formation periods, which would induce serial correlation in the constituents of portfolios. Therefore when we measure returns to a K month holding strategy we skip K months before reforming portfolios. This always ensures returns for successive momentum portfolios do not overlap, and for symmetric strategies, or when $J < K$, it also ensures that portfolio formation periods do not overlap.

We apply tests to the original 1965–1989 period studied by Jegadeesh and Titman (1993) and to the extended period 1965–2005. For both periods we study two samples, all NYSE and AMEX stocks, as in the original study of Jegadeesh and Titman (1993) and in the Appendix we report results for the full sample of NYSE, AMEX and NASDAQ stocks. Data on individual stock returns and market indices are taken from CRSP monthly files.

IV. Results

Our NYSE/AMEX sample differs slightly from that of Jegadeesh and Titman (1993) because we exclude firms with less than 24 months of returns data, for reasons explained above, and so the first step is to investigate whether this could itself directly affect the evidence for momentum. We report in Panel A of Table 1 results for our sample using raw returns for the same horizon that is used by Jegadeesh and Titman (1993). It can be seen that excluding stocks with less than 24 months of returns data makes no significant difference to the evidence. For example in the 1965–1989 period, we find that the 6 × 6 strategy of going long in “winners” and short in

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observed, if there are return reversals at short horizons, but should make little difference at intermediate and longer horizons.

“losers” generates a 0.93% abnormal return per month, significant at the 99% level, whereas Jegadeesh and Titman report that the same strategy yielded monthly profits of 0.95%, also significant at the 99% level.

[Table 1 around here]

In Panel B of Table 1 we report results for a sample period extended up to December 2005. Momentum appears to be just as much in evidence in the extended sample period as it was in the original 1965-1989 period. For example the same 6×6 strategy now yields an average return of 0.78% per month, again significant at the 99% level. In Table A1 in the Appendix we report results for the same two sample periods where NASDAQ stocks are also included. For the shorter sample period, inclusion of NASDAQ stocks weakens, but does not eliminate, the evidence for momentum. However for the period 1965-2005, although point estimates of the returns to a momentum strategy remain largely positive, the estimates are statistically significant for only three strategies. Jegadeesh and Titman (2001) include NASDAQ firms and find that momentum is still significant, but this is for a sample period that ended in 1997. They also exclude firms from all exchanges that have a share price under $5 or a market capitalization below the smallest NYSE decile cut-off point. Given the typical characteristic of NASDAQ stocks, we conjecture that simply excluding them may have much the same effect as excluding stocks on this criterion from all exchanges. Why momentum is so much in evidence in the class of stocks traded on the main exchanges, but not in the smaller stocks typically traded on NASDAQ, is itself an interesting question for future research. But whatever the reason that including NASDAQ stocks weakens the evidence for momentum, the fact remains that there is evidence of momentum that is as significant as ever in the

NYSE/AMEX sample extended to 2005. A momentum trading strategy can be applied to the universe of NYSE/AMEX stocks alone and the question remains: how can the profits to such a strategy be explained?

In Table 2 we report results for the same trading strategies except that demeaned returns (as defined in Section 2) are used in place of raw returns to both rank stocks and measure subsequent performance.

[Table 2 around here]

In can be seen in Table 2 that the momentum effects that were present in Table 1 largely vanish when we remove the cross-sectional variation in unconditional expected returns. There is now no evidence of significant positive returns for any momentum trading strategy in the full period. For the sub-period 1965-1989, there are only three combinations of J and K for which a momentum strategy delivers significant profits. We infer that the success of momentum strategies applied to raw returns is not explained by time-varying returns but by the fact they pick stocks with high unconditional returns.

A different approach to determining whether the success of the momentum strategy is due to time-varying returns or to the fact that it simply picks stocks with high unconditional means, is to compare the performance of portfolios selected on one criterion or the other. Of course full sample means cannot be used in a trading rule in practice but the objective of this horse race is to investigate the source of the returns to a momentum trading strategy, not to compare the profits on two feasible trading strategies. In Figure 1 we trace returns over 3-12 months on two winner-loser portfolios, one selected each month on the basis of raw returns measured over the last

3-12 months, and the other on the basis of their unconditional means estimated over the whole sample, with no account taken of recent time variation. It is clear for all horizons that a strategy based on unconditional means, and that ignores recent momentum, is consistently more successful than one based on recent performance. For a horizon of 3 months, the unconditional portfolios beat the momentum portfolios in 87% of months, at 6 months this figure in 88%, 9 months 89%, and at 12 months this figure rises to 95%.

[Figure 1 around here]

If recent momentum is successful because it is a noisy measure of unconditional means then portfolios formed on unconditional means should not only be more successful on average but also returns to the strategy should be less volatile. This expectation is confirmed. For example over all four symmetric strategies, on 33% of start dates the conditional momentum strategy delivers negative returns, but on only 1% of start months does the selection of stocks on the basis of unconditional means deliver negative returns. For 3×3 strategy, the standard deviation of returns on conditional momentum strategies is 3.5%, and for unconditional momentum strategies is 2.1%; for 6×6, the corresponding standard deviations are 2.4%, and 1.7%; for 9×9, they are 2%, and 1.6%; for 12×12, the figures are 1.7%, and 1.5%.

[Figures 2 and 3 around here]

A final implication of this explanation for momentum is that when winner-loser portfolios are constructed on the basis of raw returns we should observe that long positions are overweight in stocks with high unconditional returns and short positions are overweight in stocks with low unconditional returns. In Figures 2 and 3, we trace the percentage of firms from the top 25 and top 50 percentile of unconditional means that appear in winner and loser portfolios, measured by raw returns, for each formation period. It can be seen that this prediction is largely confirmed. For 96% of start dates, across all symmetric strategies, the percentage of top 50 percentile of unconditional mean stocks is greater in winner portfolios than loser portfolios. For 89% of start dates stocks from the highest 25 percentile of unconditional returns are a larger percentage of winner portfolios than loser portfolios.

V. Conclusion

There is compelling evidence that a momentum trading strategy is profitable, at least when applied to the universe of NYSE/AMEX stocks, but the reasons for its success are unclear. Is it profitable because of time-varying returns or does it simply reflect the cross-sectional variation in unconditional expected returns? The contribution of this paper is to report evidence that attempts to distinguish between these two explanations. We decompose raw returns into a term that reflects unconditional expected returns and a residual. We sidestep the problem of specifying a specific model of unconditional expected returns by measuring these as simply the full sample mean return on each stock. We then apply the conventional tests to the demeaned returns and find that there is no evidence for momentum in this series.

If it is the cross-sectional dispersion in unconditional expected returns that explains momentum in raw returns then this has two further implications. Firstly, we should expect to see that “winner” portfolios tend to select stocks with high unconditional returns and “loser” portfolios tend to select low unconditional returns stocks, and this prediction is confirmed. Secondly, if the reason that portfolios of recent “winners” subsequently outperform is because they select stocks with relatively high unconditional returns then portfolios of stocks with high means measured over the full sample should on average do even better. On the other hand this latter strategy discards information in recent returns, and hence should deliver lower profits if the key to the success of "winner" portfolios is that they exploit momentum. We report that portfolios formed on the basis of full sample means are systematically more profitable, providing further support for the hypothesis that the success of momentum strategies simply reflects the cross-sectional dispersion of expected returns.

We conclude on a note of caution. We are able to attribute the profitability of momentum trading strategies to the cross-sectional variation in expected returns, but we employ an atheoretical empirical measure of expected returns. The evidence to date is that momentum cannot be explained by using a conventional model of expected returns, for example the three factor Fama-French model. It will only be possible to claim to have thoroughly vindicated the efficient markets model when evidence for momentum vanishes after extracting the cross-sectional dispersion in expected returns, where these are measured using a fully articulated model of risk pricing.

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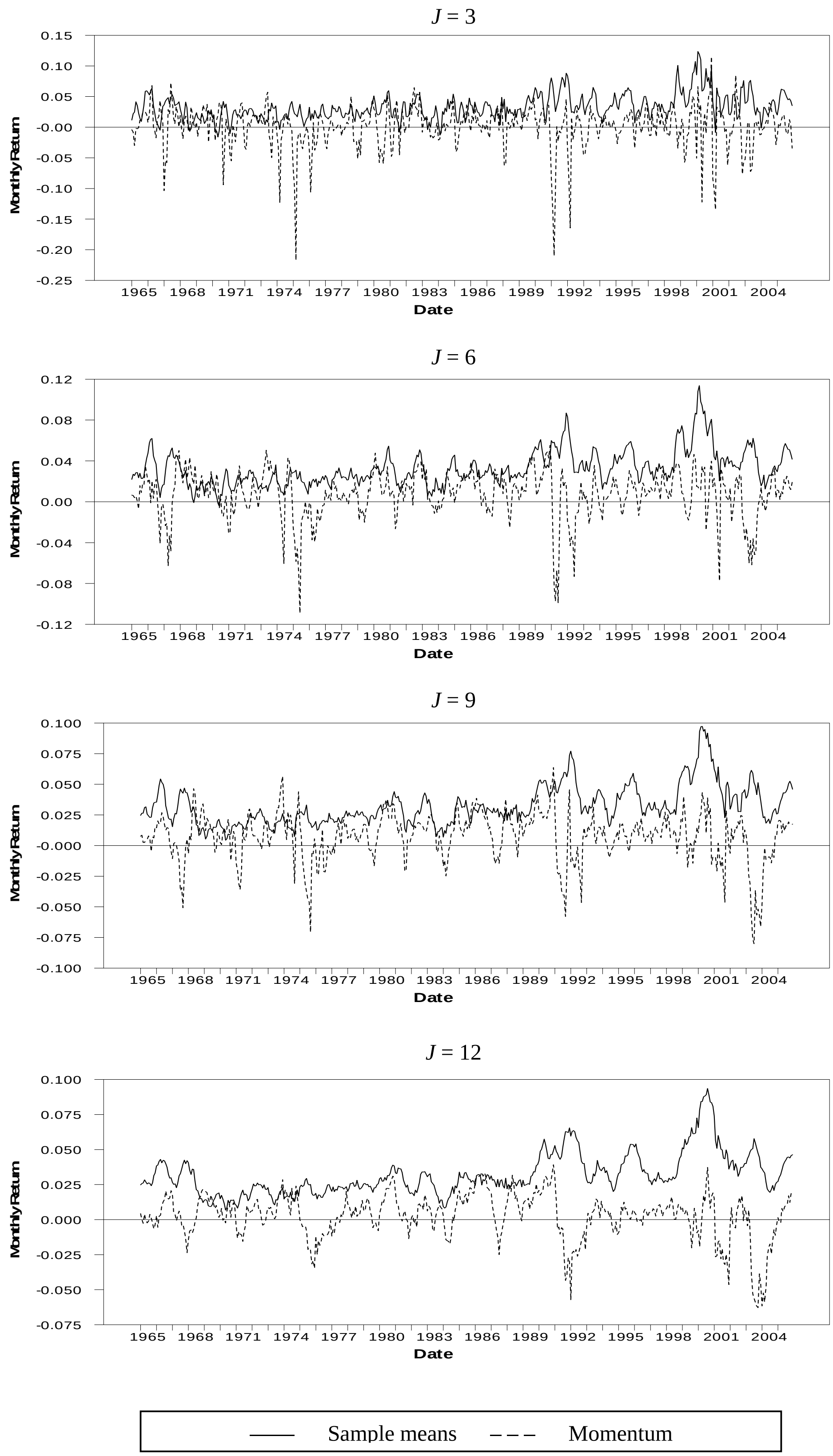
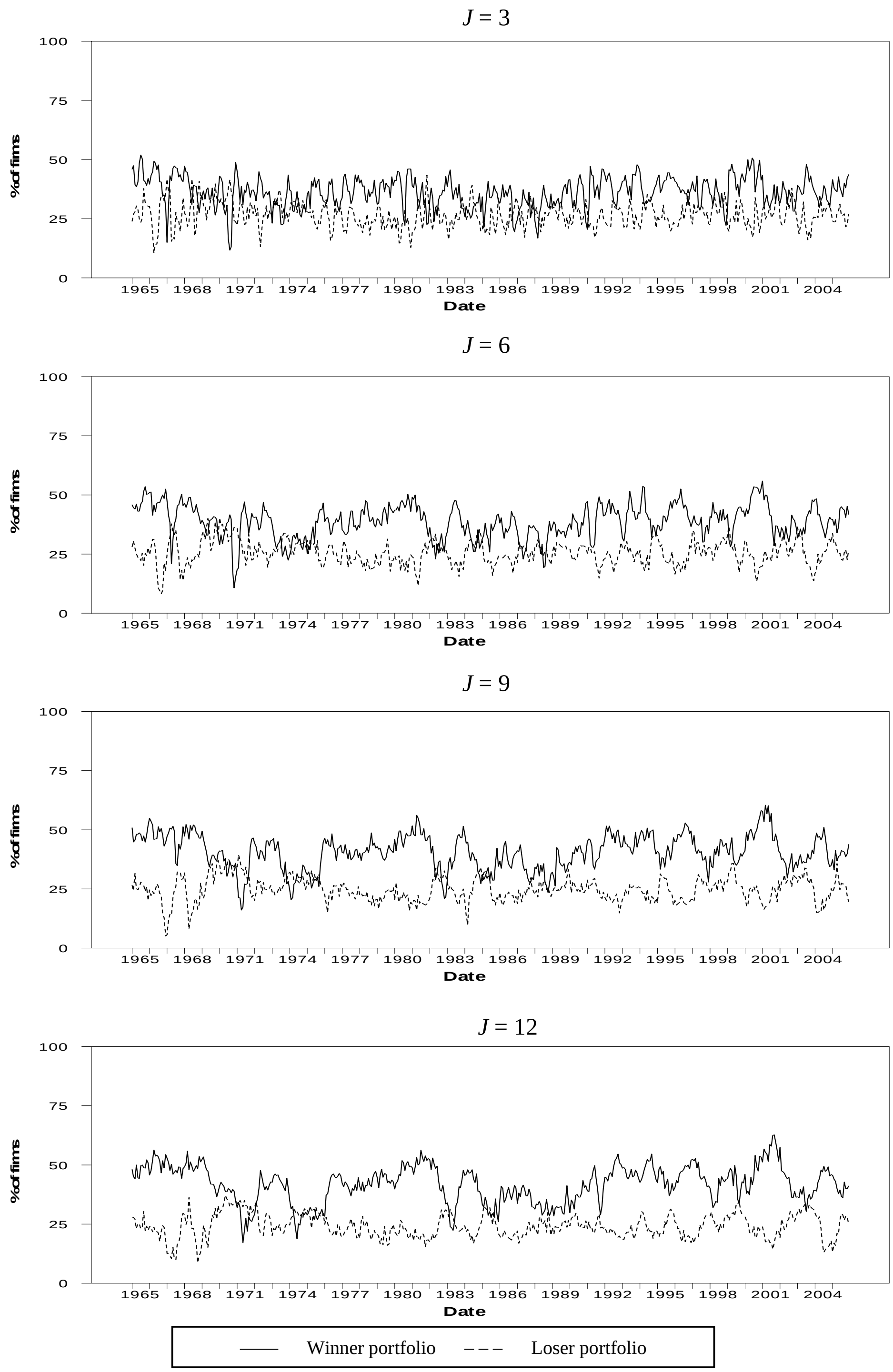
Figure 1 Time series of returns to portfolios formed on momentum and unconditional expected returns



Notes: This figure compares the time-series of returns on winner-loser portfolios ranked on the basis of recent momentum with those ranked on sample means. The dashed line shows the monthly returns of momentum portfolios based on *J*-month past returns and held for *J* months. The solid line represents the monthly returns of portfolios ranked by sample means held for *J* months. The sample includes all NYSE and AMEX stocks on monthly CRSP files with more than twenty-four return observations available over the sample period, January 1965 – December 2005.

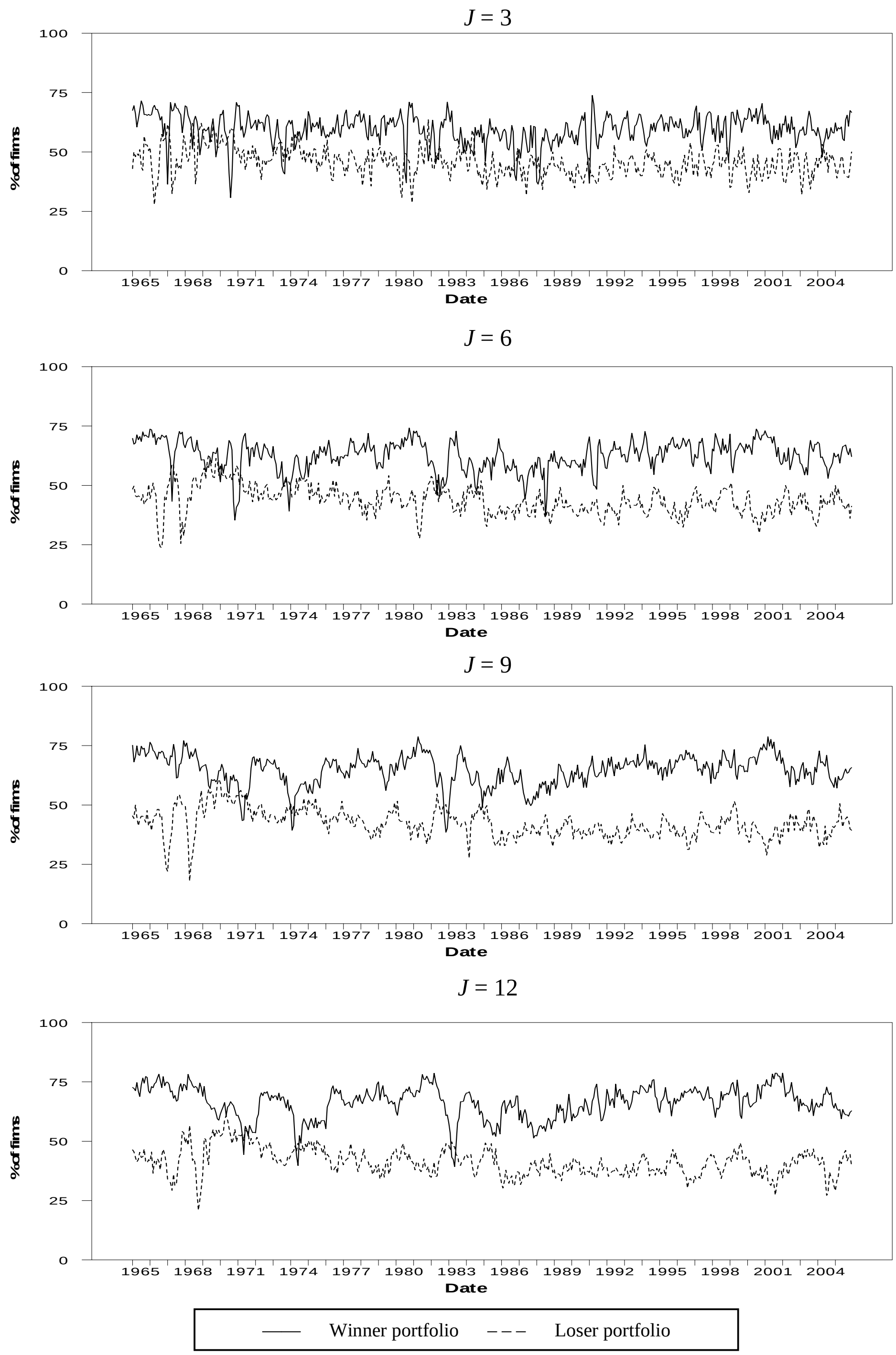
Figure 2 Time series of the percentages of firms in the winner/loser portfolio (based on *J*-month raw returns) from the top 25 percentile firms in their unconditional means



Notes: This figure shows the time series evolution of the percentages of firms in the winner/loser portfolios from the top 25 percentile firms in their unconditional means.

Portfolios are formed based on past *J*-month raw returns. The sample includes all NYSE and AMEX stocks on monthly CRSP files with more than twenty-four return observations available over the sample period, January 1965 – December 2005.

Figure 3 Time series of the percentages of firms in the winner/loser portfolio (based on *J*-month raw returns) from the top 50 percentile firms in their unconditional means



Notes: This figure shows the time series evolution of the percentages of firms in the winner/loser portfolios from the top 50 percentile firms in their unconditional means. Portfolios are formed based on past *J*-month raw returns. The sample includes all NYSE and

AMEX stocks on monthly CRSP files with more than twenty-four return observations available over the sample period, January 1965 – December 2005.

Table 1

Profitability of relative strength portfolios based on raw returns, NYSE/AMEX

		Panel A: 1965-1989				Panel B: 1965-2005			
J	*K* =	3	6	9	12	3	6	9	12
3	Winner	0.0131	0.0153	0.0166	0.0162	0.0134	0.0149	0.0171	0.0158
		(2.96)	(3.48)	(3.55)	(3.92)	(4.11)	(4.64)	(5.26)	(4.90)
3	Loser	0.0111	0.0094	0.0086	0.0079	0.0127	0.0108	0.0099	0.0091
		(2.08)	(2.06)	(1.60)	(2.24)	(3.00)	(2.92)	(2.53)	(2.74)
3	Winner-Loser	0.0020	0.0059	0.0080	0.0083	0.0007	0.0042	0.0072	0.0067
		(0.68)	(2.63)	(3.08)	(3.69)	(0.27)	(2.10)	(3.28)	(2.92)
6	Winner	0.0166	0.0174	0.0177	0.0163	0.0166	0.0170	0.0182	0.0156
		(3.68)	(3.97)	(3.81)	(4.22)	(5.11)	(5.41)	(5.83)	(5.33)
6	Loser	0.0099	0.0082	0.0066	0.0085	0.0109	0.0093	0.0088	0.0097
		(1.81)	(1.73)	(1.22)	(1.99)	(2.47)	(2.49)	(2.21)	(2.67)
6	Winner-Loser	0.0067	0.0093	0.0110	0.0077	0.0056	0.0077	0.0094	0.0059
		(2.09)	(3.62)	(3.51)	(3.00)	(2.00)	(3.68)	(3.76)	(2.40)
9	Winner	0.0183	0.0188	0.0172	0.0160	0.0188	0.0187	0.0176	0.0152
		(3.99)	(4.27)	(3.59)	(4.37)	(5.71)	(5.85)	(5.44)	(5.66)
9	Loser	0.0081	0.0064	0.0075	0.0092	0.0099	0.0085	0.0099	0.0115
		(1.46)	(1.34)	(1.35)	(1.96)	(2.22)	(2.19)	(2.38)	(2.92)
9	Winner-Loser	0.0102	0.0123	0.0096	0.0068	0.0088	0.0102	0.0077	0.0037
		(3.19)	(4.81)	(3.30)	(2.34)	(3.18)	(4.46)	(3.09)	(1.44)
12	Winner	0.0189	0.0182	0.0160	0.0154	0.0185	0.0175	0.0163	0.0144
		(4.08)	(4.20)	(3.50)	(4.05)	(5.62)	(5.53)	(5.29)	(5.26)
12	Loser	0.0066	0.0080	0.0082	0.0100	0.0092	0.0101	0.0110	0.0125
		(1.20)	(1.61)	(1.39)	(2.20)	(2.07)	(2.54)	(2.50)	(3.24)
12	Winner-Loser	0.0124	0.0102	0.0078	0.0054	0.0093	0.0074	0.0053	0.0018
		(3.99)	(4.04)	(2.51)	(2.24)	(3.37)	(3.13)	(1.91)	(0.77)

This table reports the profitability of selected relative strength portfolios based on raw returns. In each month *t*, *J*-month/*K*-month ($J \times K$) portfolios are formed in the following way. *J*-month cumulative returns are calculated based on a ranking in ascending order of stocks according to their previous *J*-month returns. The top decile of the sorted stocks is labeled the 'winner' portfolio and the bottom decile the 'loser' portfolio. The 'winner–loser' portfolio reports the strategy of going long in winners and short in losers. The monthly cumulative returns on these three portfolios are reported. Panel A contains the returns in the Jegadeesh and Titman (1993) sample period, January 1965 – December 1989. Panel B presents the returns in the extended January 1965 – December 2005 sample period. The portfolios are equally-weighted at formation date. Portfolio formation takes place immediately after ranking is done. The *t*-statistics are given in parentheses. Each sample consists of all NYSE and AMEX stocks on monthly CRSP files with more than twenty-four return observations available over the sample period.

Table 2

Profitability of relative strength portfolios based on unexpected returns, NYSE/AMEX

		Panel A: 1965-1989				Panel B: 1965-2005			
J	*K* =	3	6	9	12	3	6	9	12
3	Winner	-0.0026	-0.0006	0.0007	0.0007	-0.0019	-0.0004	0.0015	0.0007
		(-1.82)	(-0.45)	(0.56)	(0.45)	(-1.76)	(-0.43)	(1.37)	(0.59)
3	Loser	-0.0004	-0.0027	-0.0026	-0.0048	0.0018	-0.0007	-0.0011	-0.0028
		(-0.22)	(-1.67)	(-1.42)	(-3.68)	(0.90)	(-0.40)	(-0.68)	(-1.60)
3	Winner-Loser	-0.0021	0.0021	0.0033	0.0056	-0.0038	0.0003	0.0026	0.0035
		(-0.76)	(0.98)	(1.34)	(2.46)	(-1.46)	(0.13)	(1.17)	(1.48)
6	Winner	0.0002	0.0010	0.0013	0.0008	0.0007	0.0015	0.0023	0.0003
		(0.16)	(0.73)	(0.85)	(0.51)	(0.55)	(1.30)	(2.12)	(0.21)
6	Loser	-0.0011	-0.0029	-0.0041	-0.0032	0.0007	-0.0011	-0.0016	-0.0015
		(-0.51)	(-1.72)	(-2.12)	(-1.95)	(0.31)	(-0.67)	(-0.87)	(-0.83)
6	Winner-Loser	0.0013	0.0039	0.0054	0.0039	0.0000	0.0026	0.0039	0.0018
		(0.44)	(1.68)	(1.84)	(1.68)	(0.00)	(1.25)	(1.55)	(0.68)
9	Winner	0.0015	0.0019	0.0003	-0.0006	0.0018	0.0018	0.0010	-0.0014
		(0.90)	(1.37)	(0.24)	(-0.39)	(1.56)	(1.65)	(0.90)	(-1.14)
9	Loser	-0.0019	-0.0051	-0.0030	-0.0022	0.0006	-0.0019	0.0000	0.0006
		(-0.89)	(-2.94)	(-1.58)	(-1.09)	(0.26)	(-1.01)	(0.01)	(0.28)
9	Winner-Loser	0.0033	0.0071	0.0033	0.0016	0.0013	0.0037	0.0010	-0.0020
		(1.11)	(2.91)	(1.24)	(0.60)	(0.46)	(1.62)	(0.38)	(-0.71)
12	Winner	0.0015	0.0008	-0.0011	-0.0014	0.0015	0.0009	-0.0007	-0.0021
		(0.96)	(0.61)	(-0.86)	(-1.03)	(1.26)	(0.83)	(-0.70)	(-1.74)
12	Loser	-0.0038	-0.0032	-0.0022	-0.0011	-0.0003	0.0001	0.0016	0.0022
		(-1.87)	(-1.81)	(-1.03)	(-0.60)	(-0.14)	(0.06)	(0.76)	(1.05)
12	Winner-Loser	0.0053	0.0040	0.0010	-0.0003	0.0018	0.0008	-0.0024	-0.0043
		(1.85)	(1.73)	(0.36)	(-0.13)	(0.66)	(0.33)	(-0.85)	(-1.61)

This table reports the profitability of selected relative strength portfolios based on unexpected returns. In each month *t*, *J*-month/*K*-month ($J \times K$) portfolios are formed in the following way. *K*-month cumulative returns are calculated based on a ranking in ascending order of stocks according to their previous *J*-month returns. The top decile of the sorted stocks is labeled the 'winner' portfolio and the bottom decile the 'loser' portfolio. The 'winner–loser' portfolio reports the strategy of going long in winners and short in losers. The monthly cumulative returns on these three portfolios are reported. Panel A contains the returns in the Jegadeesh and Titman (1993) sample period, January 1965 – December 1989. Panel B presents the returns in the extended January 1965 – December 2005 sample period. The portfolios are equally-weighted at formation date. Portfolio formation takes place immediately after ranking is done. The *t*-statistics are given in parentheses. Each sample consists of all NYSE and AMEX stocks on monthly CRSP files with more than twenty-four return observations available over the sample period.

Appendix

Table A1

Profitability of relative strength portfolios based on raw returns, NYSE/AMEX/NASDAQ

		Panel A: 1965-1989				Panel B: 1965-2005			
J	*K* =	3	6	9	12	3	6	9	12
3	Winner	0.0117	0.0143	0.0147	0.0152	0.0129	0.0152	0.0169	0.0163
		(2.56)	(3.22)	(3.05)	(3.73)	(3.27)	(4.02)	(4.74)	(4.13)
3	Loser	0.0145	0.0109	0.0107	0.0090	0.0186	0.0148	0.0137	0.0126
		(2.69)	(2.26)	(1.97)	(2.33)	(4.09)	(3.52)	(3.31)	(3.36)
3	Winner-Loser	-0.0028	0.0034	0.0040	0.0063	-0.0057	0.0005	0.0032	0.0038
		(-1.06)	(1.62)	(1.57)	(2.65)	(-2.08)	(0.23)	(1.36)	(1.50)
6	Winner	0.0154	0.0167	0.0167	0.0148	0.0176	0.0182	0.0181	0.0160
		(3.34)	(3.70)	(3.50)	(3.74)	(4.49)	(4.97)	(5.23)	(4.07)
6	Loser	0.0132	0.0109	0.0085	0.0105	0.0171	0.0146	0.0126	0.0141
		(2.36)	(2.20)	(1.53)	(2.49)	(3.51)	(3.33)	(2.94)	(3.53)
6	Winner-Loser	0.0022	0.0059	0.0083	0.0043	0.0005	0.0037	0.0055	0.0019
		(0.71)	(2.37)	(2.82)	(1.75)	(0.17)	(1.62)	(2.14)	(0.69)
9	Winner	0.0176	0.0184	0.0165	0.0149	0.0191	0.0187	0.0173	0.0149
		(3.75)	(4.12)	(3.40)	(4.00)	(4.82)	(4.94)	(4.95)	(4.40)
9	Loser	0.0118	0.0091	0.0091	0.0111	0.0162	0.0136	0.0138	0.0155
		(2.11)	(1.83)	(1.60)	(2.43)	(3.33)	(3.08)	(3.05)	(3.58)
9	Winner-Loser	0.0058	0.0093	0.0074	0.0037	0.0029	0.0051	0.0035	-0.0006
		(1.83)	(3.61)	(2.67)	(1.44)	(0.93)	(2.05)	(1.32)	(-0.22)
12	Winner	0.0185	0.0180	0.0151	0.0150	0.0189	0.0174	0.0163	0.0142
		(3.93)	(4.07)	(3.21)	(3.94)	(4.75)	(4.61)	(4.87)	(4.24)
12	Loser	0.0099	0.0098	0.0102	0.0116	0.0150	0.0147	0.0145	0.0164
		(1.78)	(1.94)	(1.75)	(2.58)	(3.12)	(3.29)	(3.16)	(3.69)
12	Winner-Loser	0.0086	0.0082	0.0049	0.0034	0.0040	0.0027	0.0017	-0.0021
		(2.84)	(3.53)	(1.72)	(1.49)	(1.28)	(1.01)	(0.65)	(-0.75)

This table reports the profitability of selected relative strength portfolios based on raw returns. In each month *t*, *J*-month/*K*-month ($J \times K$) portfolios are formed in the following way. *J*-month cumulative returns are calculated based on a ranking in ascending order of stocks according to their previous *J*-month returns. The top decile of the sorted stocks is labeled the 'winner' portfolio and the bottom decile the 'loser' portfolio. The 'winner–loser' portfolio reports the strategy of going long in winners and short in losers. The monthly cumulative returns on these three portfolios are reported. Panel A contains the returns in the Jegadeesh and Titman (1993) sample period, January 1965 – December 1989. Panel B presents the returns in the extended January 1965 – December 2005 sample period. The portfolios are equally-weighted at formation date. Portfolio formation takes place immediately after ranking is done. The *t*-

statistics are given in parentheses. Each sample consists of all NYSE, AMEX and NASDAQ stocks on monthly CRSP files with more than twenty-four return observations available over the sample period.

Table A2

Profitability of relative strength portfolios based on unexpected returns, NYSE/AMEX/NASDAQ

		Panel A: 1965-1989				Panel B: 1965-2005			
J	*K* =	3	6	9	12	3	6	9	12
3	Winner	-0.0046	-0.0016	-0.0012	-0.0008	-0.0036	-0.0013	0.0001	-0.0005
		(-3.03)	(-1.24)	(-0.80)	(-0.50)	(-2.06)	(-0.88)	(0.06)	(-0.25)
3	Loser	0.0049	0.0005	0.0007	-0.0014	0.0086	0.0042	0.0038	0.0020
		(2.52)	(0.30)	(0.39)	(-0.93)	(3.93)	(2.07)	(1.94)	(1.04)
3	Winner-Loser	-0.0094	-0.0021	-0.0019	0.0007	-0.0122	-0.0055	-0.0037	-0.0025
		(-3.50)	(-0.93)	(-0.73)	(0.25)	(-4.42)	(-2.49)	(-1.59)	(-0.91)
6	Winner	-0.0022	-0.0009	-0.0006	-0.0021	-0.0003	0.0005	0.0002	-0.0018
		(-1.36)	(-0.65)	(-0.35)	(-1.31)	(-0.18)	(0.36)	(0.16)	(-0.96)
6	Loser	0.0044	0.0017	0.0005	0.0007	0.0081	0.0053	0.0040	0.0050
		(2.00)	(0.98)	(0.24)	(0.47)	(3.14)	(2.36)	(1.83)	(2.50)
6	Winner-Loser	-0.0065	-0.0027	-0.0011	-0.0028	-0.0084	-0.0048	-0.0038	-0.0068
		(-2.13)	(-1.07)	(-0.34)	(-1.10)	(-2.57)	(-2.02)	(-1.45)	(-2.45)
9	Winner	-0.0009	0.0000	-0.0019	-0.0029	0.0002	-0.0001	-0.0016	-0.0038
		(-0.51)	(-0.02)	(-1.20)	(-1.93)	(0.11)	(-0.07)	(-1.29)	(-2.23)
9	Loser	0.0043	0.0010	0.0014	0.0022	0.0087	0.0054	0.0057	0.0069
		(1.97)	(0.51)	(0.68)	(1.15)	(3.40)	(2.28)	(2.45)	(2.75)
9	Winner-Loser	-0.0052	-0.0010	-0.0033	-0.0051	-0.0085	-0.0055	-0.0073	-0.0107
		(-1.62)	(-0.37)	(-1.10)	(-1.78)	(-2.73)	(-2.08)	(-2.60)	(-3.27)
12	Winner	-0.0007	-0.0013	-0.0037	-0.0033	-0.0005	-0.0021	-0.0032	-0.0052
		(-0.41)	(-0.93)	(-2.45)	(-2.42)	(-0.29)	(-1.30)	(-2.67)	(-3.10)
12	Loser	0.0031	0.0025	0.0031	0.0036	0.0076	0.0074	0.0073	0.0085
		(1.47)	(1.39)	(1.43)	(2.03)	(3.06)	(3.04)	(2.96)	(3.21)
12	Winner-Loser	-0.0038	-0.0038	-0.0068	-0.0069	-0.0081	-0.0094	-0.0105	-0.0136
		(-1.26)	(-1.57)	(-2.26)	(-2.77)	(-2.65)	(-3.32)	(-3.62)	(-4.02)

This table reports the profitability of selected relative strength portfolios based on unexpected returns. In each month *t*, *J*-month/*K*-month ($J \times K$) portfolios are formed in the following way. *K*-month cumulative returns are calculated based on a ranking in ascending order of stocks according to their previous *J*-month returns. The top decile of the sorted stocks is labeled the 'winner' portfolio and the bottom decile the 'loser' portfolio. The 'winner–loser' portfolio reports the strategy of going long in winners and short in losers. The monthly cumulative returns on these three portfolios are reported. Panel A contains the returns in the Jegadeesh and Titman (1993) sample period, January 1965 – December 1989. Panel B presents the returns in the extended January 1965 – December 2005 sample period. The portfolios are equally-weighted at formation date. Portfolio formation takes place immediately after ranking is done. The *t*-statistics are given in parentheses. Each sample consists of all NYSE, AMEX and NASDAQ stocks on monthly CRSP files with more than twenty-four return observations available over the sample period.