Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing

Bruce D. Grundy[a] and J. Spencer Martin[b]

Key words: factor loadings, hedging, momentum

JEL classification: G11, G12

First Draft: May 1997

Current Draft: May 1998

All comments welcome.

[a] The Wharton School, 2300 Steinberg Hall-Dietrich Hall, University of Pennsylvania, Philadelphia, PA 19104-6367 USA Office: (215) 898-3004 Fax: (215) 898-6200 grundy@wharton.upenn.edu

[b] The Wharton School, 2300 Steinberg Hall-Dietrich Hall, University of Pennsylvania, Philadelphia, PA 19104-6367 USA Office: (215) 898-1587 Fax: (215) 898-6200 martin33@wharton.upenn.edu

---

The authors thank Michael Brandt, Morris Davis, Sandy Grossman, Joe Gyourko, Don Keim, Lubos Pastor and the participants in the 2nd Annual Australian GSM Finance Conference and seminars at Boston College, the Federal Reserve Board of Governors, the SEC, Arizona State, U. Mississippi, U. Miami and the Wharton School for their comments. We are especially grateful to Craig MacKinlay for many lengthy discussions on this subject. Previous versions of this work were circulated under the title "Momentum: Fact or factor? Momentum investing when returns have a factor structure." We retain the rights to all errors. The first author appreciates the financial support of the Geewax-Terker Research Program in Financial Instruments.

Abstract

It is well established that recent prior winner and loser stocks exhibit return continuation; a momentum strategy of buying recent winners and shorting recent losers appears profitable in the post 1945 era. In contrast, the risk exposure of such a strategy has not been well understood; the strategy's unconditional average risk exposure can be deceptive. The stock selection method of a momentum strategy guarantees that large and time varying factor exposures will be borne in accordance with the performance of the common risk factors during the periods in which stocks were ranked to determine their winner/loser status. Because the factors themselves display trivial momentum, extreme factor realizations induce noise which obscures the study of the momentum phenomenon. This noise is penetrated in two ways. First, measurements of the factor exposure of momentum strategies are made during both formation and investment periods. Raw returns to the strategies are adjusted for factor risk with two striking results: the momentum phenomenon is remarkably stable across subperiods in the *entire* time series of post 1926 stock returns; and factor models can explain around ninety-five percent of the variability of returns on portfolios of the top and bottom ten percent of prior winners and losers, but cannot explain their mean returns. Second, alternative momentum strategies are studied which base winner or loser status on stock-specific return components over some ranking period. Such strategies are *more* profitable than those based on total returns. Evidence is also presented that neither industry effects nor cross-sectional differences in expected returns are the primary cause of the observed momentum phenomenon.

1 Introduction

Jegadeesh and Titman (1993) document momentum: stocks whose returns in recent months place them in the top/bottom decile of prior return performance tend to outperform/underperform other stocks in subsequent months. This study further investigates both the risks and the possible sources of the reward to a short-term momentum strategy which is long prior winners and short prior losers. In terms of risk, we document and explain the strategy's dynamic factor exposure. We show that the strategy's average profitability cannot be explained as a reward for bearing this dynamic exposure to the three factors of the Fama and French (1993) model, nor by cross-sectional variability in stocks' average returns, nor by exposure to industry factors. The strategy's profitability reflects momentum in the stock-specific component of returns.

The dynamics of the changing factor exposure of a momentum strategy are particularly straightforward in a one-factor CAPM-like setting. If the market outperforms T-bills, winners (losers) will tend to be stocks with betas above one. Thus, following up markets, a momentum strategy will tend to place a positive beta bet on the market; i.e., the strategy will go long in stocks with betas above one and short in stocks with betas below one. Conversely, following down markets, a momentum strategy will tend to involve a negative beta bet on the market. We model and document in a multifactor setting the natural and significant correlation between a momentum strategy's factor loadings and the factor realizations during the period in which stocks were ranked as relative winners versus losers. These dynamic factor loadings induce variability in the strategy's returns that can obscure its profitability. When risk adjusted, the strategy's profitability is remarkably stable across subperiods—even in the pre-1945 period when the strategy's mean raw return is negative.

Over the 1926 through 1995 period a momentum strategy would have earned an average monthly "return" (profit per dollar long) of 0.44% (with an associated t-statistic of 1.83). The mean is -5.85% in Januaries and $+1.01\%$ in non-Januaries. Hedging out the strategy's dynamic exposure to size and market factors would have removed 78.6% of the monthly return variance, and would have increased the mean monthly return to 1.34% (with an associated t-statistic of 12.11). Similar results are found for the post 1965 period after hedging the strategy's dynamic exposure to the three factors of the Fama-French model. The increase in the mean return that accompanies the reduction in variability is primarily the result of hedging out the strategy's almost consistently losing bet against the size effect in January—the strategy goes short in prior losers, and prior losers tend to have become extremely small firms.

A full understanding of the source of the risk-adjusted profitability of a momentum strategy remains an open question. Conrad and Kaul (1997) argue that stocks with relatively high/low realized returns will tend to be stocks with relatively high/low average returns, and hence conjecture that a momentum strategy's average profitability simply reflects cross-sectional variability in average returns. If the two- and three-factor models we investigate provide an adequate control for risk, then the Conrad-Kaul conjecture is moot. To address the alternate possibility that these asset-pricing models are incomplete, we use each stock as its own control for risk. Even after subtracting each stock's mean return from its return during the investment period, the momentum strategy's mean return remains statistically and economically significant.

The risk-adjusted profitability of a momentum strategy must reflect momentum in a component of stock returns not associated with exposure to the factors considered in the risk-adjustment itself; namely the market, size and distress factors. Moskowitz (1997) concludes that the profitability of a momentum strategy cannot be explained either by its exposure to these Fama-French factors or by momentum in the stock-specific component of returns, but is explained by momentum in industry factors. We document that, although the returns to an industry-based momentum strategy are consistent with an intra-industry lead-lag effect, industry momentum alone does not explain the profitability of momentum trading strategies.

Consistent with our conclusion that momentum profits are, at least in part, due to momentum in the stock-specific component of returns, much empirical research documents patterns in the stock price reaction to firm-specific information; e.g., Bernard (1992), La Porta (1996) and Chan, Jegadeesh and Lakonishok (1996). The theoretical models of momentum due to Barberis, Shleifer and Vishny (1996), Daniel, Hirshleifer and Subrahmanyam (1997) and Hong and Stein (1997) focus on imperfect formation and revision of investors' expectations in response to new information. Although these models do not distinguish between expectations based on firm-specific information and on factor-related information, they could be extended such that only revisions in the former component give rise to momentum.

To the extent that the profitability of a momentum strategy reflects momentum in stock-specific returns, a traditional momentum strategy that defines winners and losers in terms of their relative total returns is suboptimal. We compare the profitability of a strategy that defines winners and losers in terms of their relative stock-specific returns to the profitability of a strategy that takes long/short positions in stocks that are winners/losers on a total return basis but are *not* also winners/losers on a stock-specific return basis. The stock-specific return strategy is significantly more profitable than this alternate strategy.

The study proceeds as follows. Section 2 describes the details of the total return momentum strategy investigated and the history of monthly returns thereon. Section 3 models the theoretical relation between factor realizations and both the factor-related and the stock-specific components of the returns on winners/losers. Section 4 empirically investigates the dynamic factor exposure of a total return momentum strategy. Section 5 documents the profitability of a dynamically hedged total return momentum strategy. Section 6 investigates three candidate sources of these momentum profits: cross-sectional variability in mean returns, exposure to industry factors, and momentum in stock-specific returns. Section 7 considers the after-transactions-cost profitability of momentum investing. Section 8 contains our conclusions.

2 The Total Return Momentum Strategy

2.1 The sample of firms and the set of formation and investment periods

Winners and losers are defined as stocks in the top and bottom deciles of return performance over a six month ranking period. This ranking period is referred to as the "formation period." Only NYSE and AMEX-listed stocks contained on the CRSP monthly tape throughout the entire six months are eligible for selection as winners or losers. The subsequent investment periods are one month long and (following Asness (1995) and Fama and French (1996)) begin one month after the formation period ends. This one month gap between the formation and investment periods avoids contaminating the momentum strategy with the very short-term reversals documented in Jegadeesh (1990), Lehmann (1990), Lo and MacKinlay (1990) and Jegadeesh and Titman (1995). The strategy enters a long position in an equal-weighted portfolio of winners and a short position in an equal-weighted portfolio of losers. Consecutive formation periods thus have a five month overlap. The first formation period is 1/26–6/26, and the last is 12/94–5/95. The returns to the strategy are therefore observed monthly from 8/26 through 7/95.[1]

During the 1/26–6/26 formation period each performance decile contained 52 NYSE stocks. Hence each 8/26 investment month winner/loser portfolio contained 52 NYSE stocks. By the final formation period, the addition of AMEX stocks and the growth in the number of listed firms meant that each decile contained 329 NYSE/AMEX stocks.

2.2 The ranking criterion

Let $r_{f\tau}$ denote the month τ risk-free rate. Let $r_{i\tau}$ denote the month τ return in excess of the risk-free rate on stock i. Prior empirical work defines winners and losers in terms of their compounded total return over the formation period; i.e., for the formation period preceding investment month t stocks are ranked on $\prod_{\tau=t-7}^{t-2}(1+r_{f\tau}+r_{i\tau})$. We implement a variant of this traditional strategy by selecting winners and losers on the basis of their *cumulative* monthly return over the six month formation period; i.e., we rank stocks on $\sum_{\tau=t-7}^{t-2} r_{i\tau}$.

There are two benefits to ranking on cumulative returns. When *monthly* returns have a factor

[1] Firms delisted during a month do not have a return for that month recorded in the CRSP monthly returns structure. Our method of handling delistings introduces a bias against finding momentum profits. In the event of a delisting after the end of month $t-2$ but before the end of investment month t, the delisted stock is simply never invested in/shorted. Mortality rates for winners and losers can be quite high. Averaged across the 139 non-overlapping six month windows following the June- and December-end formation periods, the mean fraction of winner/loser firms delisted within these windows is 3.7% (2.9%). The six-month mortality rate for winners (losers) is as high as 16.3% (12.2%). Shumway (1997) documents that delistings for bankruptcy, insufficient capital, and other negative performance-related reasons are generally surprises, and that correct delisting returns for stocks delisted for negative reasons are both typically missing from CRSP after 1962 and large and negative. When winners are delisted, it is typically the result of a merger or takeover (76.5% of the time), and information about the acquisition is a likely cause of their superior performance during the formation period. For delisted losers, the CRSP obituary/delisting code gives the cause of death as a liquidation or other negative performance-related reason in 78.3% of cases. Our implicit perfect foresight of delistings induces a bias against finding momentum profits.

structure, defining winners and losers in terms of cumulative performance simplifies the theoretical analysis (see Section 3) of the link between semiannual formation period factor realizations and the factor loadings of winners versus losers. The second benefit is empirical. Errors in estimates of a stock's formation period factor exposure are not independent of the compounded return on that stock over the formation period. When stocks are ranked on compounded returns, a stock's winner/loser status is not independent of the error in the estimate of its factor loadings. This bias does not arise when winners and losers are defined by their relative cumulative returns.

To see the relation between compounded returns and estimated factor loadings, consider a one-factor CAPM world. Let $r_{m\tau}$ denote the excess return on the market in month τ. The compounded rate of return on stock i over the six month formation period preceding investment month t is:

$$\begin{aligned}\prod_{\tau=t-7}^{t-2}(1+r_{i\tau})-1 &= \prod_{\tau=t-7}^{t-2}(1+r_{f\tau}+\beta_i r_{m\tau}+e_{i\tau})-1\\ &= \begin{pmatrix}\text{a set of terms unrelated to the sample}\\ \text{covariance between the } e_{i\tau} \text{ and } r_{m\tau}\end{pmatrix} - \beta_i \textstyle\sum_{\tau=t-7}^{t-2} e_{i\tau} r_{m\tau}\,. \qquad (1)\end{aligned}$$

The error in a beta estimate obtained from a regression using only the six observations during the formation period is proportional to $\sum_{\tau=t-7}^{t-2} e_{i\tau}\left(r_{m\tau}-\overline{r_m}\right)$. From (1) we see that, conditional on a stock's true beta being positive, stocks whose idiosyncratic returns happen to have a positive/negative *sample* covariance with market excess returns over the estimation period are more likely to be classified as losers/winners over that period when winners and losers are judged on the basis of compounded returns.

2.3 The history of raw returns to a total return momentum strategy

Figures 1 and 2 depict the history of monthly returns to the total return momentum strategy, where 'return' means the profit per dollar long. Clearly the strategy does not earn an arbitrage profit—while notionally zero investment, it is far from riskless. Rightward cumulations of the bars at the bottom of the Figure 1 (i.e., backward through time) give the solid line. The solid line shows the profits accumulated through 7/95 starting from different investment months back to 8/26. If the strategy were always profitable, the line would slope monotonically upward from left to right. While there are extended periods of near monotonicity, there are exceptions. For example, an investor who first entered the strategy in January 1991 and continued the strategy through July 1995 would have lost 58 cents.[2]

Figure 2 shows the monthly time series in greater detail. The mean monthly return is 0.44% with an associated t-statistic of 1.83, and the strategy earns a positive return in 506 of 828 months. The insignificant overall mean is dragged down considerably by a strong negative January seasonal. The thicker black bars on the chart are Januaries. The strategy's mean January return is -5.85%, with an associated t-statistic of -4.93. Only 15 of the 69 January returns are positive. In contrast, 491 of the 759 non-January returns are positive, with a mean of 1.01% and a t-statistic of 4.44. Subperiod statistics for the strategy appear in Table 3. Together, Figures 1 and 2 show clearly that the total return momentum strategy is risky with a January seasonal in its losses. We turn now to a theoretical modeling of the dynamics of the strategy's factor exposure that give rise to such variable returns.

3 Winners versus Losers: Factor Exposure versus Stock Selection in Theory

Our theoretical results apply in any k-factor setting. Suppose that the cumulative excess return on stock i over the six month formation period preceding investment month t is described by the following two-factor model:

$$r_i = \alpha_i + \beta_i \, r_{_{EW}} \quad + \quad s_i \, OMT + e_i \, , \; \forall \; i, \tag{2}$$

where

$$r_i \equiv \sum_{\tau=t-7}^{t-2} r_{i,\tau} \quad , \quad r_{_{EW}} \equiv \sum_{\tau=t-7}^{t-2} r_{_{EW,\tau}} \, ,$$

[2] Cooper, Gutierrez and Marcum (1996) examine in detail what would have happened to an investor who had attempted in real time to use the post-1926 stock return data to identify investment strategies related to the now established book-to-market and size effects. It is interesting to ask a similar question here. Consider a 20 year old investor in 1940. Looking back over the post 1926 data, she decides to implement a contrarian strategy. After losing money almost every month for the next few decades, she abandons her earlier belief in negative autocorrelation in favor of zero autocorrelation. Although the ongoing profitability of a momentum strategy looks tempting, the losses to momentum investing in 1974 and 1975 give her pause. Finally, by January ′91 she decides that she has enough data to confidently bet on positive autocorrelation, and she switches to a momentum strategy. After then losing 58 cents with this strategy, our seventy-five year old investor goes to her grave in July 1995, penniless and confident in the knowledge that markets really are 'efficient.'

$$OMT \equiv \sum_{\tau=t-7}^{t-2} OMT_\tau \quad , \quad e_i \equiv \sum_{\tau=t-7}^{t-2} e_{i,\tau} \, ,$$

and $r_{EW,\tau}$ is the month τ excess return on an equal-weighted stock market index and OMT_τ is the month τ difference in returns on the CRSP indices of stocks in the first and tenth deciles of equity values (OMT is a mnemonic for deciles 'One Minus Ten', and decile one contains the smallest firms). The e_i are assumed cross-sectionally $i.i.d.\, N(0, \sigma^2)$. The e_i are independent of both r_{EW} and OMT.

The factor loadings β_i and s_i are, respectively, stock i's *marginal* market and size factor loadings. We use returns on equal-weighted portfolios as proxies for the market and size factors because doing so simplifies the theoretical analysis of the factor exposure of an equal-weighted winner minus loser momentum strategy.

When in (2) $\alpha_i = 0$ for all i, expected returns are described by a two-factor asset pricing model. When a momentum strategy is associated with abnormal returns relative to this two-factor model, the $\alpha_i \neq 0$ for all i and are, instead, a function of past performance.[3]

Stocks with realized returns in the top and bottom deciles of formation period total return performance may be characterized by differences in each of the three components that produce their excess returns; i.e., by differences in their 'abnormal' returns (α_i), in their factor-related returns ($\beta_i \, r_{EW} + s_i \, OMT$), and in their stock-specific returns (e_i). To focus on the latter two differences, we assume throughout the remainder of Section 3 that $\alpha_i = 0$ for all i. We also assume that the cross-sectional distribution of the β_i and s_i is bivariate normal, with

$$\begin{pmatrix} \beta_i \\ s_i \end{pmatrix} \sim N \left(\begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\beta^2 & \sigma_{\beta s} \\ \sigma_{\beta s} & \sigma_s^2 \end{pmatrix} \right)$$

Conditional on the realized values of r_{EW} and OMT, the cumulative formation period excess returns on the individual stocks are cross-sectionally distributed $N(r_{EW}, \mathcal{V})$, with

$$\mathcal{V} := \sigma_\beta^2 \, r_{EW}^2 + \sigma_s^2 \, (OMT)^2 + 2\sigma_{\beta s} \, r_{EW} \, OMT + \sigma_e^2.$$

[3] Lo and MacKinlay (1990) and Jegadeesh and Titman (1995) investigate contrarian strategies using weekly data and examine the extent to which α_i depends on stock i's lagged residual return, the factor component of stock i's lagged return, and the lagged residuals on other stocks.

The top 10% of firms in the population will have realized returns exceeding the population mean return by at least 1.282 standard deviations.

3.1 Factor-related returns and a stock's winner/loser status

Let the subscripts W and L denote the equal-weighted portfolios of winner and loser stocks. Let $E\{\beta_W \,|\, r_{EW}, OMT\}$ denote the expected beta of the stocks in the winner portfolio conditional on the formation period factor realizations:

$$E\{\beta_W \,|\, r_{EW}, OMT\} := E\left\{\beta_i \,|\, r_{EW}, OMT\,,\, r_i > r_{EW} + 1.282\sqrt{\mathcal{V}}\right\}.$$

Using the properties of a truncated Normal distribution, we show in Appendix A that

$$E\{\beta_W \,|\, r_{EW}, OMT\} = 1 + 1.754\,\frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\sqrt{\mathcal{V}}}\,. \tag{3}$$

If both factor realizations happen to be zero, ranking on total returns will be identical to ranking on the stock-specific component of returns. Since stock-specific returns and factor loadings are independent, ranking on stock-specific returns amounts to ranking on a criterion unrelated to factor loadings. Hence, the expected beta of the winner portfolio in this event is unity. Substitution of $r_{EW} = OMT = 0$ into (3) gives this result immediately.

When r_{EW} is nonzero, the expected beta of stocks in the winner portfolio will be greater (less) than unity as r_{EW} is greater (less) than zero. The winner portfolio's beta is naturally bounded above/below by the average of the top/bottom 10% of all betas. As r_{EW} increases, ranking stocks on the basis of their total returns becomes closer and closer to ranking only on betas:

$$\lim_{r_{EW}\to\infty} E\{\beta_W \,|\, r_{EW}, OMT\} = 1 + 1.754\,\sigma_\beta = E\left\{\beta_i \,|\, \beta_i > 1 + 1.282\,\sigma_\beta\right\}\,.$$

For example, suppose $\sigma_\beta = \sqrt{0.133} = 0.365$. The expected beta of the winner portfolio will approach 1.64 in an extreme up market, and 0.36 in an extreme down market. As r_{EW} decreases, ranking stocks on their total returns becomes closer to a reverse beta ranking. Relation (3) makes clear that, provided $\sigma_{\beta s} \neq 0$, the realization of the OMT factor will also affect the expected beta of the portfolio of winner stocks. Section 4 empirically confirms the nonlinear direct and cross effects implicit in relation (3).

Figure 3 depicts the relation between the conditional expected marginal beta of the winner portfolio and the factor realizations over a six month formation period. Figure 3 is based on the following parameter values: $\sigma_\beta^2 = 0.133$, $\sigma_s^2 = 0.154$, $\rho_{\beta s} = -0.187$, and $\sigma_e^2 = 0.066$ over a six-month interval. (These values match our empirical estimates derived from monthly returns data using the methodology described in Appendix B.) A figure corresponding to $\rho_{\beta s} = 0$ would be symmetric along both the X- and Y-axes.

Symmetric arguments describe the expected beta of the loser portfolio, $E\{\beta_L \,|\, r_{EW}, OMT\}$, and hence the conditional beta of a momentum strategy will be given by:

$$E\{\beta_W \,|\, r_{EW}, OMT\} - E\{\beta_L \,|\, r_{EW}, OMT\} = 2 \times 1.754 \, \frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} \, OMT}{\sqrt{\mathcal{V}}} \,. \tag{4}$$

To illustrate the strength of the link between factor realizations and factor loadings of a momentum strategy, assume that over some six-month formation period the realized value of r_{EW} happened to be two standard deviations greater than expected and that the OMT realization happened to be zero. Assume that over a six-month interval $r_{EW} \sim N(0.06\,,\, 0.207^2)$. (These parameter values also match sample estimates.) Substitution in (4) gives the result that the expected marginal beta of a momentum strategy is 0.714: the winners' expected beta is 1.358, the losers' is 0.642. If r_{EW} happened to be two standard deviations less than expected and again $OMT = 0$, the conditional expected beta of a winner minus loser strategy is -0.574.

Like its beta, the size loading of a total return momentum strategy also depends on the factor realizations. Let $E\{s_W \,|\, r_{EW}, OMT\}$ and $E\{s_L \,|\, r_{EW}, OMT\}$ denote the conditional expected size loadings of winner and losers stocks respectively. Appendix A shows that a momentum strategy's size loading is given by:

$$E\{s_W \,|\, r_{EW}, OMT\} - E\{s_L \,|\, r_{EW}, OMT\} = 2 \times 1.754 \, \frac{\sigma_s^2 \, OMT + \sigma_{\beta s} \, r_{EW}}{\sqrt{\mathcal{V}}} \,.$$

3.2 Stock-specific returns and a stock's winner/loser status

Let $E\{e_{_W} \,|\, r_{_{EW}}, OMT\}$ denote the expected stock-specific return component of stocks in the winner decile conditional on the formation period factor realizations:

$$E\{e_{_W} \,|\, r_{_{EW}}, OMT\} := E\left\{e_i \,|\, r_{_{EW}}, OMT\,,\, r_i > r_{_{EW}} + 1.282\sqrt{\mathcal{V}}\right\}.$$

As shown in Appendix A, our distributional assumptions imply:

$$E\{e_{_W} \,|\, r_{_{EW}}, OMT\} - E\{e_{_L} \,|\, r_{_{EW}}, OMT\} = 2 \times 1.754\, \frac{\sigma_e^2}{\sqrt{\mathcal{V}}}\,.$$

When $r_{_{EW}} = OMT = 0$, ranking on total returns is equivalent to ranking on the stock-specific component of returns. The expected stock-specific return component of winner stocks is then simply the expected value of the top 10% of stock-specific returns:

$$E\left\{e_{_W} \,|\, r_{_{EW}} = OMT = 0\right\} = 1.754\,\sigma_e = E\left\{e_i \,|\, e_i > 1.282\sigma_e\right\}\,.$$

Non-zero realizations of the factors will induce greater cross-sectional dispersion in stock returns, and less of the differences in stocks' total returns will be explained by differences in their stock-specific returns. As the factor realizations become extreme, the expected stock-specific component of the returns on winner stocks will approach the unconditional expectation of stock-specific returns; i.e., zero.

Figure 4 depicts the expected stock-specific return component of winner stocks as a function of the contemporaneous factor realizations. A comparison of Figures 3 and 4 reveals that factor realizations that induce significant factor exposure in a total return momentum strategy do not preclude that strategy from capturing the bulk of the stock-specific component of returns.

4 Factor-Related Risk and a Total Return Momentum Strategy

This section empirically investigates the strategy's factor loadings during both the formation and subsequent investment periods. The factor models considered are the two-factor model of expression (2) and the three-factor Fama-French model:[4]

$$r_{i\tau} = \alpha_i + \beta_i\, r_{m\tau} + s_i\, SMB_\tau + h_i\, HML_\tau + e_{i\tau}\,, \tag{5}$$

[4] We thank Gene Fama for providing the history of the Fama-French factors.

where $r_{m\tau}$ is the month τ excess return on the Fama-French market index, SMB_τ is the return on the size factor and HML_τ is the return on the distress factor. Since the Fama-French factors exist for the post-1963 period only, our investigation of the Fama-French model is restricted to that period. The two-factor model is investigated from 1926 on.

4.1 Formation period factor exposure

We calculate both the mean and the median of regression estimates of the formation period factor loadings of the stocks in the winner and loser portfolios. Short-window estimates use only the six monthly observations during the formation period. Long-window estimates are calculated over an up to 60 month (and at least 36 month) window, the final six months of which constitute the formation period. Thus, the first available long-window estimate of two-factor (three-factor) formation period loadings corresponds to the 7/28–12/98 formation period (the 1/66–6/66 formation period). None of this study's conclusions are affected by whether one considers median or mean factor loadings, or short or long-window estimates.

Figures 5A and 5B depict the median winner and loser stocks' long-window estimates of the formation period two-factor market and size loadings as a function of the formation period realization of the corresponding factor. Figures 5C, 5D and 5E depict the median long-window estimates of the formation period three-factor market, size and distress loadings of winner and loser stocks. As predicted by the analysis of Section 3, the winner/loser stocks' median factor loadings are increasing/decreasing in the corresponding factor realizations.

To investigate the nonlinear cross and direct effects of relation (4), we first form a time-series of beta estimates in the following manner. For t equal to each February and August from 2/29 through 2/95 we estimate the betas of each of the stocks that were winners and losers over the six-month formation periods $t-7$ through $t-2$ and had at least 36 months of returns on the CRSP tapes prior to month $t-1$. Note that the sets of winner and loser stocks are selected on the basis of their performance over non-overlapping six month formation periods. The marginal betas of each stock are the long-window estimates obtained from regressions using data over months

$\tau = \max[t-61, \text{first month in which stock has return data}], \ldots, t-2$. The beta of a total return momentum strategy over the formation period ending in month $t-2$ is then estimated as:

$$\hat{\beta}_{W-L,t} \equiv \text{median}_{i \in \mathcal{W}_t} \, \hat{\beta}_i - \text{median}_{i \in \mathcal{L}_t} \, \hat{\beta}_i \, ,$$

where $\hat{\beta}_i$ is the long-window estimate of stock i's marginal beta, and $\mathcal{W}_t/\mathcal{L}_t$ denotes the set of stocks that were winners/losers in formation period $t-7, \ldots, t-2$. In the multivariate normal setting underlying relation (4), $\hat{\beta}_{W-L,t}$ is an estimate of

$$\frac{3.508 \, \left(\theta_1^2 \sum_{\tau=t-7}^{t-2} r_{EW,\tau} + \theta_1\theta_2\theta_3 \, \sum_{\tau=t-7}^{t-2} OMT_\tau\right)}{\sqrt{\theta_1^2 \, \left(\sum_{\tau=t-7}^{t-2} r_{EW,\tau}\right)^2 + \theta_2^2 \, \left(\sum_{\tau=t-7}^{t-2} OMT_\tau\right)^2 + 2\theta_1\theta_2\theta_3 \, \left(\sum_{\tau=t-7}^{t-2} r_{EW,\tau}\right)\left(\sum_{\tau=t-7}^{t-2} OMT_\tau\right) + \theta_4^2}} \, ,$$

where $\theta_1 = \sigma_\beta$, $\theta_2 = \sigma_s$, $\theta_3 = \rho_{\beta s}$ and $\theta_4 = \sigma_e$.

We estimate $\theta_1, \ldots, \theta_4$, using nonlinear least squares. The estimates and their asymptotic standard errors are reported in Table 1. We cannot reject the null hypothesis that each of σ_β, σ_s and σ_e are non-negative at the 5% level. We can reject the null that $\rho_{\beta\, s}$ is non-negative.

It is interesting to compare the $\hat{\rho}_{\beta\, s} = -0.157$ value estimated from the nonlinear relation between the beta of a momentum strategy and the formation period market and size factor realizations with a direct estimate of the cross-sectional correlation of betas and size loadings. The details of our direct estimation are contained in Appendix B. We obtain 14 independent estimates of the cross-sectional correlation between the marginal beta and size loadings (one for each non-overlapping five year interval between 1926 and 1995). 12 of the estimates are negative. The mean of the 14 estimates is -0.187 and the associated $t-$statistic is -3.9.

Figure 5 shows clearly the increasing and nonlinear relation between a given factor's realization in the formation period and the total return momentum strategy's formation period loading on that factor. Table 1 reports the significant nonlinear direct effect of the formation period market factor realization on the strategy's beta risk as well as the significant crosseffect of the size factor realization on beta. Still, the more relevant measure of risk of a total return momentum strategy to an investor is its factor exposure during the investment period. Hence, we turn now to the investment period.

4.2 Investment period factor exposure

Although factor loadings change between the formation and investment periods, the relation between factor realizations and formation period factor loadings observed in Figure 5 does carry over to the investment period. Figure 6 portrays median short-window estimates of factor loadings of winners and losers over the 6 months beginning with the investment month. The investment period factor loadings of winner/loser stocks are increasing/decreasing in the prior *formation* period realization of the corresponding factor.

Table 2 reports the results of regressions that seek to estimate the relation between the investment period factor loadings of winner and loser stocks and the formation period factor realizations. Formation period factor realizations are characterized as either 'down', 'flat' or 'up.' 'Down' realizations are at least one standard deviation below the factor's mean. 'Flat' realizations are within one standard deviation of the mean. 'Up' realizations exceed the mean by at least one standard deviation.

Consider the following regressions: For investment months $t =$ 8/26 through 7/95,

$$\begin{aligned} r_{p,t} = \alpha_p \quad &+ \quad \beta_{p\,DOWN} D_t^{EW,down} r_{EW\,t} \quad + \beta_{p\,FLAT} D_t^{EW,flat} r_{EW\,t} \quad + \beta_{p\,UP} D_t^{EW,up} r_{EW\,t} \\ &+ \quad s_{p\,DOWN} D_t^{OMT,down} OMT_t + s_{p\,FLAT} D_t^{OMT,flat} OMT_t + s_{p\,UP} D_t^{OMT,up} OMT_t \\ &+ \quad e_{pt}; \end{aligned} \tag{6}$$

and for investment months $t =$ 8/66 through 7/95,

$$\begin{aligned} r_{p,t} = \alpha_p \quad &+ \quad \beta_{p\,DOWN} D_t^{m,down} r_{mt} \quad + \beta_{p\,FLAT} D_t^{m,flat} r_{mt} \quad + \beta_{p\,UP} D_t^{m,up} r_{mt} \\ &+ \quad s_{p\,DOWN} D_t^{SMB,down} SMB_t + s_{p\,FLAT} D_t^{SMB,flat} SMB_t + s_{p\,UP} D_t^{SMB,up} SMB_t \\ &+ \quad h_{p\,DOWN} D_t^{HML,down} HML_t + h_{p\,FLAT} D_t^{HML,flat} HML_t + h_{p\,UP} D_t^{HML,up} HML_t \\ &+ \quad e_{pt}\,, \end{aligned} \tag{7}$$

where $\delta \in \{down,\ flat,\ up\}$, and

$$D_t^{j,\delta} \quad \equiv \quad \begin{cases} 1: & \text{if } \sum_{\tau=t-7}^{t-2} r_{j\tau} \text{ was of type } \delta; \\ 0: & \text{otherwise.} \end{cases}$$

The upper portion of panel I of Table 2 reports the results of regression (6) estimated subject to the constraint that the factor loadings are not dependent on the prior formation period's factor realizations. The results of the unconstrained regression in (6) are reported in the lower portion of the panel. Factor loadings of winners/losers are significantly larger/smaller following up-factor formation period realizations than following down-factor formation period realizations. The beta of a total return momentum strategy is $+0.409$ following up market realizations and -0.452 following down. Its size loading is $+0.421$ following up OMT realizations and -0.481 following down. The $F_{4,821}$ statistic associated with a test of the null that $\beta_{p\,UP} = \beta_{p\,FLAT} = \beta_{p\,DOWN}$ and $s_{p\,UP} = s_{p\,FLAT} = s_{p\,DOWN}$ for winners/losers is 127/70, with an associated p-value of $1.81E-84$/$2.71E-51$.

The upper portion of panel II reports the results of the constrained variant of regression (7). The results of the unconstrained regression are reported in the lower portion of the panel. The Fama-French factor loadings of the winner and loser portfolios exhibit significant dynamic behavior. The $F_{6,338}$ statistic associated with the null of no dynamic behavior in winners'/losers' Fama-French factor loadings is 24/13.8, with an associated p-value of $1.12E-23$/$4.91E-14$.

This dynamic factor exposure of winner and loser portfolios is one potential cause of the inverted "U-shaped" pattern in the R^2 values reported in Table VII of Fama and French (1966). The factor loadings of the portfolios of 'average performance' stocks contained in deciles 5 and 6 of prior performance will be less dynamic than those of the extreme prior performance deciles, deciles 1 and 10. The error in an unconditional regression of returns on factor realizations will reflect both the residual in the conditional relation and the differences between conditional and unconditional factor loadings times the corresponding factor realizations. The R^2 of an unconditional regression will then be lower for winners and losers than for 'average performance' stocks.

5 The Risk-Adjusted Profitability of a Total Return Momentum Strategy

Fama and French (1996) document that a momentum strategy's profitability cannot be explained by its unconditional factor exposure. A momentum strategy may, though, spuriously appear to earn abnormal returns if it tends to load heavily on a factor when exposure to that factor requires a high return—see Chan (1988) and Jagannathan and Wang (1996). Such a possibility could explain momentum profits provided the factors themselves displayed positive momentum. Recall that a momentum strategy in month t tends to load positively on those factors that performed well in months $t-7$ to $t-2$, and to negatively weight factors that performed poorly.

The factors themselves do not exhibit significant positive momentum. Let f_{jt} denote the realization of factor j in month t and consider the regression:

$$f_{jt} = \theta_{j0} + \theta_{j1} \sum_{\tau=t-7}^{t-2} f_{j\tau} + u_{jt}. \tag{8}$$

For the r_{EW} and OMT factors and the 8/26 through 7/95 period, the θ_1 estimates are -0.0249 and -0.0305 respectively. The associated t-statistics are -1.93 and -2.21.[5] This section documents that recognizing the dynamic factor exposure of a momentum strategy tends to magnify, rather than explain away, its profitability.

5.1 Hedging the realized factor exposure of a momentum strategy

Table 3 reports both the raw and risk-adjusted profitability of a total return momentum strategy. Table 3 distinguishes between January and other months. The left-hand set of columns of Table 3 reports raw returns. Between 8/26 and 7/95 the average raw return to the strategy was an insignificant 0.44% per month. The average was brought down by losses in Januaries and throughout the volatile 1926 through 1945 subperiod. Note that outside of January, the average raw monthly return was 1.01%, with an associated t-statistic of 4.44. The standard deviation of the raw monthly returns was 6.9% per month.

Our risk-adjustment is equivalent to "hedging out" the strategy's estimated factor exposure. For the two-factor model, the factor loadings in investment month t are first estimated from the regression:

$$r_{W-L,\tau} = \alpha_{W-L} + \beta_{W-L}\, r_{EW\,\tau} + s_{W-L}\, OMT_\tau + e_{W-L,\tau}, \quad \tau = t, \ldots, t+5.$$

The estimated factor loadings corresponding to investment month t are denoted by $\hat{\beta}_{W-L,t}$ and $\hat{s}_{W-L,t}$. The risk-adjusted profit in month t is measured as $r_{W-L,t} - \hat{\beta}_{W-L,t}\, r_{EW\,t} - \hat{s}_{W-L,t}\, OMT_t$. The risk-adjusted results are reported in the center columns of Table 3.

[5] For the r_m, SMB and HML factors and the 8/66 through 7/95 period, the respective θ_1 estimates are -0.0088, 0.0126 and 0.0012 (with associated t-statistics of -0.41, 0.66 and 0.07).

Over the full 1926 through 1995 period, the strategy earned an average risk-adjusted return of 1.34% per month. The associated t-statistic of 12.11 is difficult to dismiss. This hedged strategy is profitable in 567 of 828 months, and is profitable in 43 of 69 Januaries. The strategy earns economically and statistically significant risk-adjusted profits in every subperiod, even during the tumultuous 30's. Furthermore, unlike raw returns, the strategy's risk-adjusted returns are on average positive in January. Figure 7 presents the results graphically. Hedging the total return momentum strategy's factor exposure increases the average payoff and decreases the variability of payoffs. The cause of the increase in the average payoff is twofold.

First, hedging removes the strategy's often disastrous bet against the January effect. Although the strategy's average raw return in January is -5.85%, its average risk-adjusted January return is 0.49%. Jegadeesh and Titman (1993) document both that a momentum strategy experiences negative average raw returns in January and that loser stocks are on average smaller than winners. The latter observation predicts the former given that, in January, small firms typically outperform their larger cousins.[6] Figure 8 plots January observations of the raw return to a total return momentum strategy against the return implied the strategy's loading on the OMT factor; i.e., against $\hat{s}_{W-L,t}\,OMT_t$. The strategy's poor performance in Januaries is traced clearly to its loading on the size factor.

The second cause of the hedging-induced increase in average payoffs is that hedging the strategy's dynamic factor exposure hedges out its implicit bet on momentum in the factors. In the pre-1945 period such bets happened to be particularly unlucky. For the 8/26 through 8/45 subperiod, the average non-January raw return is -0.47% per month, while the average non-January risk-adjusted return is $+1.12\%$. Estimating relation (9) for the r_{EW} and OMT factors over the 8/26 through 8/45 period gives θ_1 estimates $-.0399$ and -0.305 respectively. The associated $t-$statistics are -1.59 and -2.04. This result is also anticipated in the Jegadeesh and Titman (1993) study. In back-testing their relative strength trading strategy, Jegadeesh and Titman report that returns to the strategy over the 1927 to 1940 time period were significantly lower than returns over the 1965 to 1989 period. They conclude that such

[6] Note also that the set of stocks that are losers in the June-November formation period are likely to be prime candidates for December tax-loss selling, another possible source of abnormal January performance—see Reinganum (1983).

a result is potentially due to the market's extreme volatility and mean reversion during the earlier period.

Hedging leads to a dramatic reduction in variability. Over the full period, hedged returns display only 21.4% of the variability of raw returns to a total return momentum strategy. For winners considered separately, hedged returns display only 5.1% the variability of raw returns. For losers, only 3.2% of the raw variability remains after hedging. The efficacy of the hedge is explained by the large number of stocks in which the strategy takes long and short positions. The portfolio's risk beyond its factor exposure should (and does) tend to diversify away.[7] Note that the relative reduction in variability due to hedging is smallest for the 9/45 through 3/62 subperiod. In this subperiod, the small magnitude of the formation period factor realizations meant that a total return momentum strategy placed relatively small factor bets on what were relatively 'calm' factors; i.e., there was little factor risk to hedge out.

The results of hedging the strategy's exposure to the three Fama-French factors over the 8/66 through 7/95 period are quite similar to those of the two-factor model. These results are reported in panel II of the table. Hedging transforms a significant raw average return over this period into an even larger and more significant risk-adjusted average return of 1.48% per month. The risk-adjusted January profit is 1.66% per month on average.

5.2 Feasible hedging of the returns to a momentum strategy

In practice, one cannot implement the hedge underlying the calculation of the risk-adjusted profits reported in Table 3. To do so would require that at the beginning of each investment month one knew the factor exposure to be realized over the subsequent six months. One could feasibly hedge using factor loadings estimated from prior data. Suppose one hedged on the basis of long-window estimates of factor loadings over the prior formation period. The results of such a feasible strategy are reported in the right-most set of columns in Table 3. For investment months 2/29 through 7/95, such a feasible hedging

[7] It is perhaps surprising that the hedge is not even more effective. If the factor loadings were estimated without error, the standard deviation of the strategy's hedged returns should be that of a large equal-weighted portfolio of stock-specific returns. The median number in the winner minus loser portfolio is 218, and the average is 314. If stock-specific returns were truly independent across stocks, then to explain a 3 to 4% standard deviation of hedged monthly returns (the value reported in Table 3) on a portfolio of 218 stocks would require that the average stock have a monthly standard deviation of stock-specific returns of 44% to 59%! In practice, winner and loser stocks' returns will reflect common industry factors that will not diversify away. This issue is examined in Section 6.

strategy would have returned an average return of 0.63% per month, with a monthly standard deviation of 5.35% and an associated t-statistic of 3.30. This simple hedge succeeds in removing 40.57% of the monthly return variation.[8]

Note that the long-window formation period estimate of the OMT loading of a winner minus loser strategy can be positive, yet the strategy can have a negative OMT loading during the investment month simply because by the end of the formation period losers have ended up being smaller than winners. When one attempts to hedge out a presumed positive, yet actually negative, bet on the OMT factor by shorting the OMT factor, one will increase, not reduce risk. In January in particular, such flawed hedging will tend to be associated with losses on both the unhedged strategy and the hedge itself. In part, the success of the feasible strategy can be traced to the fact that the estimated long-window formation period OMT loading is positive in only 19 of 66 Januaries.

Although determining the optimal feasible hedge is beyond the scope of this study, two comments are in order. First, an alternate strategy that does not suffer from the above mentioned potential problem would involve hedging by trading an offsetting portfolio of short/long positions in non-winner/non-loser stocks designed to mimic the winner/loser strategy's cross-sectional distribution of positions in firms of various sizes. This strategy would hedge the strategy's size exposure by matching on the size characteristic itself, rather than by matching on an estimate of the strategy's formation period OMT loading. The work of Daniel and Titman (1997) points to the efficacy of such a hedge. Second, one could attempt to predict changes in factor loadings between the formation and investment periods. That changes in risk are somewhat predictable is most clearly seen in a one-factor CAPM-like setting. Since beta is, in part, a measure of *relative* financial and operating leverage, the betas of winner/loser stocks should decrease/increase between the formation and investment periods. Figure 9 depicts short-window estimates of the formation and investment period beta loadings of winners and losers for the 25 most positive and 25 most negative non-overlapping formation period realizations of the excess return on the market. The predicted changes in beta risk are dramatically borne out in the data.

[8] Table 6A reports that the unhedged strategy using the comparable set of stocks, namely those with at least 36 potential months of data at the end of each formation period, earned an average of 0.26% per month, with a monthly standard deviation of hedged returns of 6.94% and an associated t-statistic of 1.07.

5.3 Industry concentration and the risk of momentum investing

The two- and three-factor models employed in this study are models designed to explain the cross-sectional dispersion in the *expected* returns on stock. One might, more correctly, refer to them as "priced-factor" models. Non-priced factors can also explain returns. For example, winner and loser portfolios will sometimes contain a disproportionately large number of firms from within a given industry. After hedging out the priced-factor exposure of a momentum strategy, there can still be considerable remaining risk if the e_i terms of expressions (2) and (6) reflect common industry characteristics of winners and/or losers.

As one example of industry concentration, consider set of firms underlying the outlier in Figure 6C. This outlier corresponds to the investment period beginning 2/85. Over the preceding 7/84–12/84 formation period, fully 15% of the losers were Oil and Gas Extraction firms. Only 0.7% of winners (and only 3.5% of all firms) fell into this 2-digit SIC code grouping. The price of West Texas Intermediate fell from $20 to $16.50 per barrel during this period. Winners tended to be energy consumers. While only 1.1% of losers were classified as Electric, Gas and Sanitary Services firms, 19.9% of the winners (and only 4.4% of all firms) fell into this industry grouping. During the subsequent six months beginning 2/85, energy consumers had a much higher sensitivity to the market than did energy producers. For the median winner/loser stock the short-window investment period estimated beta was 3.9/$-$3.2.[9]

An industry component in the determination of stocks' winner/loser status has two effects. First, errors in the estimates of the factor loadings of winner/loser stocks will not be independent of each other, and hence mean or median estimated factor loadings will be less efficient estimates than otherwise.

[9] Other examples of industry concentration in the winner and loser portfolios are:

i). Formation period 2/37–7/37.

- Local & Interurban Passenger Transit: 12.7% of losers, 0% of winners and 1.4% of all firms.
- Primary Metal Industries: 3.8% of losers, 21.8% of winners and 7.9% of all firms.

ii). Formation period 1/81–6/81.

- Oil and Gas Extraction: 15.2% of losers, 1.5% of winners and 3.2% of all firms.
- Apparel & Other Textile Products: 0.7% of losers, 8.1% of winners and 2.1% of all firms.

Second, even if the total return strategy's market, size and distress factor exposures can be accurately estimated and hedged out, the remaining risk will not be purely firm-specific. The component of winner and losers stocks' individual returns due to common industry effects will not diversify away.

Industry effects are then a second potential cause of the inverted "U-shaped" pattern in the R^2 values reported in Table VII of Fama and French (1966). The extreme prior performance deciles, namely losers and winners, are likely to contain a larger common industry component than the portfolios of 'average performance' stocks. Since this common component will not diversify away, less of the variation in returns on portfolios of winners and losers will be explained by the three factors of the Fama-French model. For 'average performance' stocks the component of returns not related to the Fama-French factors should be largely independent across stocks, and hence should diversify away across such large portfolios. Thus an industry component in returns can increase the risk of momentum investing. Whether a priced industry factor can explain the profitability of momentum investing is considered in Section 6.2.

6 The Source of Momentum Profits

The results of Section 5 suggest that the source of momentum profits is momentum in a component of returns beyond that due to exposure to market, size and distress factors. In this section we consider three possible sources of such momentum: Momentum in some component of expected returns beyond the expected return for bearing exposure to the Fama-French factors; momentum in industry factors; and, momentum in stock-specific returns.

6.1 The Conrad-Kaul conjecture

Conrad and Kaul (1997) conclude that the success of all medium-horizon relative strength strategies is entirely due to cross-sectional dispersion of mean returns. If our two- and three-factor models adequately characterize differences in mean returns, then the risk-adjusted profitability of momentum strategies reported in Table 3 is at variance with the Conrad-Kaul conclusion. But it may be that the two-and three-factor asset pricing models employed in the risk-adjustment are flawed and there remains an additional component to stocks' expected returns. If that component is constant through time, but different across stocks, it will appear as positive momentum. One way to directly examine the Conrad-Kaul conjecture is, then, to use each stock as its own control for risk.

The center panel of Table 4 reports the profitability of a total return momentum strategy when each winner or loser stock i's investment month t return, r_{it}, is adjusted by its time series mean, $\overline{r}_i$, to give $r_{it} - \overline{r}_i$. Let n_t denote the number of firms in each performance decile over the formation period $\tau = t-7, \ldots, t-2$. The mean-adjusted profitability of the strategy reported in the center panel is 0.50% per month lower than the average raw return to the strategy.

$$\sum_{t=8/26}^{7/95} \left(\frac{\sum_{i \in \mathcal{W}_t} \overline{r}_i - \sum_{i \in \mathcal{L}_t} \overline{r}_i}{n_t} \right) \Big/ 828 = 0.50\% \, .$$

Even after making this adjustment, the average non-January return to the strategy remains significantly profitable overall. The mean-adjusted non-January profits are significant in each subperiod other than the tumultuous 30's.

Estimating the expected return on a stock by its time series mean is natural whenever that time-series is long. But whenever a winner achieves that status because it is a take-over target, or a loser stock is delisted soon after achieving that status, the time series is cut short. Realized returns that are far from those expected will tend to give rise to both winner/loser status and a short return history. Those short histories will overrepresent extreme positive or negative return outcomes. It is, therefore, interesting to consider estimating each stock's mean return from observations outside the formation period. Let $\dot{r}_{it}$ denote the time series mean return on stock i omitting $r_{i\,t-7}, \ldots r_{i\,t-2}$. The right-most panel in Table 4 reports the profitability after adjusting by $\dot{r}_{it}$. Note that

$$\sum_{t=8/26}^{7/95} \left(\frac{\sum_{i \in \mathcal{W}_t} \dot{r}_{it} - \sum_{i \in \mathcal{L}_t} \dot{r}_{it}}{n_t} \right) \Big/ 828 = -0.02\%$$

per month. Using the $\dot{r}_{it}$ to mean-adjust the strategy's investment month returns gives an estimate of the strategy's profitability that is indistinguishable from its raw profitability.

The conclusion to be drawn from the results in the right-most panel is that the profitability of a momentum strategy during the investment month *is* economically and statistically different from that in other months outside of the formation period. Returns in the second month after a period of extreme relative performance are on average different from returns in the other months outside that period.

6.2 Momentum and industry factors

Moskowitz (1997) concludes that momentum investment strategies are no longer profitable once one controls for the effects of industries on returns. Moskowitz examines the returns to a strategy of buying firms in industries that were winners over a past ranking period and shorting an equal dollar amount of firms in the loser industries. Firms are value-weighted within industries. Equal-weighting is employed across winner/loser industries. This strategy gives rise to significant positive returns. Moskowitz also examines the profitability of a "random industry" strategy. The random industry strategy replaces each initial long/short position in a firm by a long/short position in a firm with the same formation period return as the firm in the true winner/loser industry. Thus, the random industry strategy looks for momentum profits in firms with the same formation period returns as the firms in the winner and loser industries. Moskowitz's random industry strategy earns zero profits.

Table 5 reports the results of applying the real and random industry momentum strategies when the top and bottom three industries are defined by their cumulative value-weighted returns over various formation periods prior to investment month t. The four panels comprising the Table differ in the formation periods considered. (The 7/63 through 7/95 sample period is chosen for comparability with Moskowitz's work.) The upper three rows of each of the four panels report results when firms are value-weighted within each industry. Since the results in the preceding Sections of this study examine returns on equal-weighted portfolios of winner and loser stocks, the results with equal-weighting within each industry are reported in the lower three rows of each panel. Note that in each panel the returns to the random industry strategy are less variable—the portfolio is better diversified.

Panel I of Table 5 examines the strategies' profitability when winner and loser industries are defined over the six months $t-7,\ldots,t-2$ relative to investment month t. Recall that as a simple control for the documented very short-term reversals in stock returns, all the results in the prior Sections of this study reflect a one month interval between the end of the formation period and the investment month. Given a one month interval between the formation period and the investment month, neither random *nor* real value-weighted industry strategies earn momentum profits. Statistics on the difference between the returns to real and random industry momentum strategies are reported in the right-most portion of Table 5. The difference in the profitability of the value-weighted real and random strategies is insignificant.

Moskowitz considers only formation periods that are contiguous with investment periods and observes that much of the profitability of an industry momentum strategy comes in the month immediately after the formation period. Panel II of Table 5 reports the results when winner and loser industries are defined over the six months $t-6,\ldots,t-1$ relative to investment month t. Absent a one month interval between the formation period and the investment month, value-weighted real industries do earn significant momentum profits, value weighted random industries do not, and the difference is statistically significant.

Panel III employs an eleven month ranking period chosen to match the length of the formation period in Fama and French (1996). There is a one month interval between the formation and investment periods and, again, the difference in the profitability of value-weighted real and random industry momentum strategies is not significant. Interestingly, both the value-weighted random *and* real industry strategies earn significant momentum profits given a $t-12,\ldots,t-2$ formation period. When the formation period is lengthened to $t-12,\ldots,t-1$ and, hence, formation and investment periods are contiguous, then the real industry momentum strategy significantly outperforms its random cousin—see Panel IV.

The return during the month immediately following the formation period plays a pivotal role in the conclusion that a value-weighted real industry momentum strategy outperforms a random industry strategy. Although firms in the real and random industries have nearly identical performance over the formation period, firms in random industries turn out to be on average smaller than firms in the real winner and loser industries.[10] Hence, the return on firms in random industries may be more impacted

[10] Value-weighting random industry firms highlights errors on the CRSP tapes. *Genisco Technology Corp.* (CUSIP 37229810) implemented a 1-for-10 reverse stock split in December 1994. The price per share rose from $0.50 to $6.75 between November and December, and is recorded as a $1,250\%$ return that month.

by bid-ask bounce immediately following the month in which the replacement firms earn returns comparable to the returns of the firms in the real winner and loser industries. Bid-ask bounce will be more pronounced in returns on equal-weighted portfolios than in value-weighted returns. Returns during the month immediately following the formation period will also reflect any intra-industry lead-lag effect. Moskowitz presents evidence consistent with such an effect, but dismisses it after controlling for firm size. But it is not clear that the lead-lag effect in question must reflect large stocks leading small. It may simply be that industry-related momentum is purely an intra-industry lead-lag effect unrelated to firm size.

Turning to the results on equal-weighted real and random industry return strategies, we see that although there is evidence consistent with some industry component to momentum profits (average raw returns to the real industry strategy are significantly greater than those to the random industry strategy), the random industry strategy does earn statistically significant raw returns in months other than January. The cause of any difference in the risk-adjusted profitability of equal-weighted real and random industry strategies remains an open question.

Note that the formation period performance of stocks in the top and bottom industries, especially value-weighted industries, will be less extreme than the formation period performance of that same number of top and bottom-performing firms from across all industries. As Table VII of Fama and French (1996) shows, momentum profits are rapidly attenuated as one moves away from the extreme performance deciles. A momentum strategy based on stocks contained in the top and bottom deciles of prior peformance but not contained in the winner and loser industries may well outperform the real industry momentum strategy.

What is clear from Table 5 is that it is premature to conclude that firms that have similar performance to, but may or may not be contained in, the winner or loser industries do not earn momentum

---

Genisco, with an aggregate market value of only $383,000, had formation period returns that matched those of a firm in a loser industry. The firm it matched accounted for 9.75% of its industry's market value. Thus Genisco's mis-stated return of $+1,250\%$ received a 0.0975 weighting in calculating the random industry value-weighted return. Since the industry was a loser, shorting this stock with this weight contributed -121.875% to the value-weighted return on the random industry. Equal weighting across the three loser industries meant that this one error reduced the random industry momentum profits by -40.625% in that investment month!

profits, and hence that "momentum profits are non-existent for the random industries, ..., consistent with the *true* industry being the important component behind momentum profits" [Moskowitz (1997, p. 15)].

6.3 Momentum and stock-specific returns

We compare the profitability of a total return momentum strategy to the profitability of two alternate momentum strategies. Each momentum strategy designates winners and losers as the top and bottom decile of stocks according to a ranking criterion. The factor-related return momentum strategy ranks stocks on the basis of an estimate of the factor component of the formation period returns. The stock-specific return momentum strategy ranks stocks on the basis of an estimate of their formation period non-factor related returns.

These alternate momentum strategies were implemented by first estimating the parameters of the following variants of two- and three-factor models. For each investment month t, the following regressions were for all NYSE and AMEX stocks i with monthly returns on the CRSP tapes over at least the 36 month window $t-37$ to $t-2$: For $\tau = \max[t-61, \text{ month of first observation on CRSP}], \ldots, t-2$,

$$r_{i\tau} = \alpha_{0i} + \alpha_{1i}D_\tau + \beta_i r_{EW,\tau} + s_i OMT_\tau + e_{i\tau}$$

and

$$r_{i\tau} = \alpha_{0i} + \alpha_{1i}D_\tau + \beta_i r_{m,\tau} + s_i SMB_\tau + h_i HML_\tau + e_{i\tau},$$

where

$$D_\tau = \begin{cases} 1: & \text{if } \tau < t-7; \\ 0: & \text{otherwise.} \end{cases}$$

The stock-specific return momentum strategy picks winners and losers on the basis of the estimated α_{0i}.[11] The factor-related return momentum strategy ranks the stocks (from which it

[11] Note that a stock's 'alpha' over months $t-61$ though $t-8$ is equal to $(\alpha_{0i} + \alpha_{1i})$. A stock's 'alpha' over months $t-7$ though $t-2$ is α_{0i}. If one viewed the 'alpha' over months $t-61$ though $t-8$ as an estimate of the expected deviation of the stock's return from that implied by the two-factor model, then one might be tempted to use $[\alpha_{0i} - (\alpha_{0i} + \alpha_{1i})]$ as an estimate of stock-specific performance over the formation period. Winners would then often be stocks with large *negative* values of α_{1i}; e.g., stocks which experienced a period of normal returns following an extended period of poor performance. Such a "momentum" strategy turns out to actually select stocks similar to those selected by the long-run contrarian strategy of DeBondt and Thaler (1985).

will determine the winners/losers to be acquired/shorted at the beginning of investment month t) on the basis of $\sum_{\tau=t-7}^{t-2}\left(\hat{\beta}_i r_{EW,\tau} + \hat{s}_i OMT_\tau\right)$ for the two-factor model, and on the basis of $\sum_{\tau=t-7}^{t-2}\left(\hat{\beta}_i r_{m,\tau} + \hat{s}_i SMB_\tau + \hat{h}_i HML_\tau\right)$ for the three-factor model.

Tables 6A and 6B each contain four vertical panels, the first three of which correspond to the three variants of a momentum strategy. The risk-adjusted profitability of a stock-specific return strategy is marginally greater than that of the total return strategy, and markedly greater than the factor-related return strategy's risk-adjusted profitability. Note that the biggest difference between the risk-adjusted profitability of the total return strategy and the stock-specific return strategy occurs in the most volatile subperiod, 1929 through 1945.

Winners and losers on the basis of a total return ranking are often also winners and losers on the basis of a ranking of stock-specific returns. Averaged over all formation periods and over both the winner and loser groups, the overlap between stocks ranked in the extreme deciles of performance on the basis of the two ranking criteria is 78% when stock-specific returns are estimated relative to the two-factor model. The overlap is 75% when stock-specific returns are estimated relative to the three-factor model. The overlap is smallest in the 1929 through 1945 subperiod.

To focus on the distinction between stock-specific returns and total returns, we determine the set of stocks that were winners/losers on the basis of a total return ranking but were *not* also winners/losers on the basis of the stock-specific return ranking. In each investment month t we form equal-weighted portfolios of the set of stocks that were winners/losers *only* on a total return basis. The winner portfolio is purchased and an equal dollar value of the loser portfolio shorted. The 'returns' from this fourth momentum strategy are reported in the right-most panels of Tables 6A and 6B. There is no overlap in the stocks underlying the results reported in the second and fourth vertical panels.

Comparing the second and fourth panels of Table 6A we see that, relative to the two-factor model, the risk-adjusted difference in the returns to the stock-specific return strategy and the strategy that excludes stocks that were winners or losers on the basis of their stock-specific performance averages 0.97% per month. This difference in means is 5.38 times its estimated standard deviation. The risk-adjusted profits measured relative to the three-factor model and compared in the second and fourth vertical panels of Table 6B are also higher for the stock-specific return momentum strategy, but are not significantly different.

The risk-adjusted profitability of the fourth strategy may reflect the fact that the stocks included in the fourth strategy because their stock-specific performance did not place them in an extreme decile are, given their extreme total return performance, likely to fall into the second and ninth deciles of stock-specific performance. As suggested by Table VII of Fama and French (1996), stocks in these deciles are also likely to be associated with significant momentum profits.

7 Transactions Costs

Even if transactions costs preclude undertaking a momentum strategy per se, they do not help us explain the economics of the empirical regularity. Nor are they relevant to the choice between two stocks that differ only in their prior returns–marginal transactions costs are zero. The profitability of a momentum strategy reported in Table 3 argues for tilting a portfolio's weights toward recent winners and away from recent losers.

The average 'return' to actually undertaking the zero investment, total return momentum strategy reported in Table 3 is overstated by the transactions costs of implementing the strategy. Note that the turnover of positions implicit in the strategy is far from 100% per month because the formation periods corresponding to investment months t and $t+1$ will share five months in common. Stocks with extreme performance over a six-month formation period are likely to still qualify as winners/losers when the start of the formation period is shifted forward by one month. On average, only 39.908% of the winners are sold at the end of the investment month, and only 36.233% of the short positions in the losers are closed out at the end of the month.

Given these turnover probabilities, Table 7 reports the level of round-trip transactions costs that would offset the strategy's average raw and risk-adjusted returns, as well as the level of transactions costs necessary to make the strategy's returns after-transactions-costs statistically insignificant at the 5% level. Table 7 breaks the strategy's total return into two parts: the return from a zero investment strategy that finances equal-weighted long positions in winner stocks by borrowing at the T-bill rate; and, the return from a second zero investment strategy that uses the proceeds of equal-weighted short-sales of loser stocks to acquire T-bills.

Only an investor whose round-trip costs were less than 1.5% would conclude that his net profits were statistically significant. For the small firms contained in the winner and loser portfolios, Keim and Madhavan (1998) estimate transactions costs of this size and more. Interestingly, in the more recent 8/66–7/95 period, the strategy's profits come from the short positions. Even ignoring transactions costs, the long positions do not earn statistically significant risk-adjusted profits.[12]

8 Conclusions

The voluminous work documenting the apparent abnormal returns to momentum strategies presents a serious challenge to our extant asset pricing models.[13] This paper has documented the statistically significant dynamics of the factor exposure of strategies based on momentum in total returns. Since the factor component makes up one part of a stock's total return, a bet on momentum in total returns is, in part, a bet on momentum in the factors themselves. The mechanics of the strategy place such a bet quite naturally. Those stocks with higher/lower loadings on the factors that performed relatively well during the formation period are more likely to enter the winner/loser portfolio, and the larger the magnitude of the formation period factor realizations, the more likely this event will occur. The sign and the size of the strategy's factor loadings reflect the sign and size of the corresponding factor realizations during the formation period.

Hedging the strategy's dynamic exposure to a size and a market factor reduces the variability of its monthly returns by 78.6%. Further, since the factors themselves do not display positive momentum, this reduction in variability is achieved without sacrificing the strategy's historical average return. Rel-

[12] If, though, winners and losers are defined after first ranking firms on their compounded, rather than their cumulative, monthly returns during the formation period, winners so-defined do earn significant risk-adjusted before-transactions-costs returns during this more recent period.

[13] Beyond the papers already referenced, the reader is referred to Carhart (1997), Grinblatt, Titman and Wermers (1995), Rouwenhorst (1996) and Wermers (1996).

ative to either the version of a two-factor asset pricing model investigated over the 8/26–7/95 period or the three-factor Fama-French model investigated over the 8/66–7/95 period, a total return momentum strategy would have earned a statistically and economically significant risk-adjusted 'return' of more than 1.3% per month. This risk-adjusted profitability is remarkably stable across subperiods and the poor performance of the unhedged strategy in January is traced to its exposure to a size factor.

Our focus on the decomposition of total returns into their factor and stock-specific components suggests that a strategy ranking stocks and selecting winners and losers on the basis of formation period stock-specific returns should be more profitable than the more familiar total return based momentum strategy. Our evidence is strongly suggestive that such a stock-specific return momentum strategy does dominate a total return momentum strategy. We also conclude that the profitability of momentum investing is not entirely explained by either cross-sectional variability in required returns or as a reward for bearing industry risk.

To mature from youthful anomaly to middle-aged factor, a data regularity must have a sufficient risk component that the Shleifer and Vishny (1997) "limits to arbitrage" prove binding. The risk-adjusted returns associated with momentum investing do not imply an arbitrage opportunity—the hedged total return momentum strategy lost money in 261 of 828 months. Although transactions costs may explain the persistence of a 1.3% per month anomaly, they do not explain the equilibrium underlying that anomaly. Assuming that the anomaly endures, then, quite appropriately, it will enter the lexicon of finance as a 'factor' whose economics are as well understood as the SMB and HML factors: If it remains a fact, it becomes a factor.[14]

[14] Appendix C considers two settings where autocorrelation in stock-specific returns could be viewed as a factor.

Table 1. Formation Period Beta of Total Return Momentum Strategy vs. Factor Realizations: Nonlinear Estimation

For each month, t, the Total Return Momentum Strategy uses the top and bottom deciles of $\sum_{\tau=t-7}^{t-2} r_{i\tau}$ to designate winners and losers from among all NYSE and AMEX stocks i on the monthly CRSP tape. $r_{i\tau}$ is the month τ return on stock i in excess of the risk-free rate. The factor loadings of each winner and loser stock with returns for months $t-37$ to $t-2$ are estimated from the following regression:

$$r_{i\tau} = \alpha_i + \beta_i \, r_{EW\,\tau} + s_i \, OMT_\tau + e_{i\tau}\,,\ \tau = t-61, \ldots, t-2.$$

$r_{EW\,\tau}$ is the month τ excess return on the equal-weighted market index. OMT_τ is the month τ difference in returns on the CRSP indices of decile one (small) stocks and decile ten (large) stocks. The formation period beta of the total return momentum strategy is $\hat{\beta}_{W-L,t} = \underset{i\in\mathcal{W}_t}{\text{median}}\,\hat{\beta}_i - \underset{i\in\mathcal{L}_t}{\text{median}}\,\hat{\beta}_i$, where $\mathcal{W}_t$ ($\mathcal{L}_t$) denotes the set of winner (loser) stocks in formation period $t-7, \ldots, t-2$. The expected relation of the strategy's beta to the factor realizations is given by $E\{\beta_{W-L,t}|r_{EW}, OMT\} = 3.508\ \frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\sqrt{\mathcal{V}}}$, where $\mathcal{V} = \sigma_\beta^2 r_{EW}^2 + \sigma_s^2 OMT^2 + 2\,\sigma_{\beta s} r_{EW}\, OMT + \sigma_e^2$. The table shows a nonlinear least squares estimation of the following relation for dates t equal to each February and August from February 1929 through February 1995:

$$\hat{\beta}_{W-L,t} = \frac{3.508\left(\theta_1^2 \sum_{\tau=t-7}^{t-2} r_{EW\,\tau} + \theta_1\theta_2\theta_3 \sum_{\tau=t-7}^{t-2} OMT_\tau\right)}{\sqrt{\theta_1^2\left(\sum_{\tau=t-7}^{t-2} r_{EW\,\tau}\right)^2 + \theta_2^2\left(\sum_{\tau=t-7}^{t-2} OMT_\tau\right)^2 + 2\,\theta_1\theta_2\theta_3\left(\sum_{\tau=t-7}^{t-2} r_{EW\,\tau}\right)\left(\sum_{\tau=t-7}^{t-2} OMT_\tau\right) + \theta_4^2}}$$

Thus, $\hat{\theta}_1$ estimates σ_β, $\hat{\theta}_2$ estimates σ_s, $\hat{\theta}_3$ estimates $\rho_{\beta\,s}$, and $\hat{\theta}_4$ estimates σ_e.

	θ_1	θ_2	θ_3	θ_4
Dependent Variable: $\beta_{W-L,t}$				
estimate	0.4481	0.8455	-0.1573	0.3414
s.e.	0.1279	0.5139	0.0639	0.2057
(t-stat)	(3.50)	(1.65)	(-2.46)	(1.66)

Table 2. Relation Between Investment Period Factor Exposure of Winners and Losers and Formation Period Factor Realizations

For each month, t, the total return momentum strategy uses the top and bottom deciles of $\sum_{\tau=t-7}^{t-2} r_{i\tau}$ to designate winners and losers (W and L) from among all NYSE and AMEX stocks i on the monthly CRSP tape. $r_{i\tau}$ is the month τ return on stock i in excess of the risk-free rate. For each equal-weighted portfolio $p \in \{W-L, W, L\}$ time series r_{pt}, Panel I estimates, for months $t =$ August 1926 through July 1995, $r_{pt} = \alpha_p + \beta_p \, r_{EW\,t} + s_p \, OMT_t + e_{pt}$ and

$$r_{pt} = \alpha_p \quad + \quad \beta_{pDOWN} \, D_t^{EW,down} \, r_{EW\,t} + \beta_{pFLAT} \, D_t^{EW,flat} \, r_{EW\,t} + \beta_{pUP} \, D_t^{EW,up} \, r_{EW\,t} + s_{pDOWN} \, D_t^{OMT,down} \, OMT_t + s_{pFLAT} \, D_t^{OMT,flat} \, OMT_t + s_{pUP} \, D_t^{OMT,up} \, OMT_t + e_{pt}$$

Panel II estimates, for $t =$ August 1966 through July 1995, $r_{pt} = \alpha_p + \beta_p \, r_{mt} + s_p \, SMB_t + h_p \, HML_t + e_{pt}$ and

$$r_{pt} = \alpha_p \quad + \quad \beta_{pDOWN} \, D_t^{m,down} \, r_{mt} + \beta_{pFLAT} \, D_t^{m,flat} \, r_{mt} + \beta_{pUP} \, D_t^{m,up} \, r_{mt} + s_{pDOWN} \, D_t^{SMB,down} \, SMB_t + s_{pFLAT} \, D_t^{SMB,flat} \, SMB_t + s_{pUP} \, D_t^{SMB,up} \, SMB_t + h_{pDOWN} \, D_t^{HML,down} \, HML_t + h_{pFLAT} \, D_t^{HML,flat} \, HML_t + h_{pUP} \, D_t^{HML,up} \, HML_t + e_{pt}$$

$r_{EW\,t}$ is the month t excess return on the equal-weighted market index; OMT_t is the month t difference in returns on the CRSP indices of decile one (small) stocks and decile ten (large) stocks; r_{mt} is the excess return of the Fama-French market index; SMB_t is the size factor; and HML_t is the book-to-market factor. Dummy variable $D_t^{j,\delta}$ is: 1 if $\sum_{\tau=t-7}^{t-2} r_{j\tau}$, the cumulative performance of factor j over months $t-7$ to $t-2$, was of type $\delta = \{down, flat, up\}$ defined, respectively, as {at least 1 standard deviation below its mean, within 1 standard deviation of its mean, at least 1 standard deviation above its mean}; and 0 otherwise.

	Winner Minus Loser			Winners			Losers		
Parameter	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)
I. 2-Factor Model									
Intercept	0.873	.209	(4.18)	0.336	.114	(2.93)	-0.538	.120	(-4.48)
β	-0.190	.037	(-5.16)	0.953	.020	(47.34)	1.143	.021	(54.11)
s	-0.269	.033	(-8.24)	0.012	.018	(0.65)	0.281	.019	(14.95)
Intercept	0.926	.166	(5.56)	0.344	.090	(3.81)	-0.582	.104	(-5.59)
β_{DOWN}	-0.452	.041	(-10.93)	0.774	.022	(34.50)	1.227	.026	(47.45)
β_{FLAT}	-0.005	.037	(-0.14)	1.110	.020	(55.56)	1.115	.023	(48.48)
β_{UP}	0.409	.081	(5.06)	1.170	.044	(26.63)	0.760	.051	(15.03)
s_{DOWN}	-0.481	.052	(-9.24)	-0.123	.028	(-4.34)	0.358	.033	(11.03)
s_{FLAT}	-0.346	.028	(-12.25)	-0.022	.015	(-1.45)	0.324	.018	(18.35)
s_{UP}	0.421	.067	(6.24)	0.368	.037	(10.04)	-0.054	.042	(-1.27)
II. 3-Factor Model									
Intercept	1.268	.297	(4.27)	0.236	.136	(1.73)	-1.032	.230	(-4.48)
β	-0.114	.072	(-1.58)	1.082	.033	(32.53)	1.197	.056	(21.31)
s	-0.719	.105	(-6.87)	1.013	.048	(21.09)	1.732	.081	(21.37)
h	-0.653	.118	(-5.51)	0.078	.054	(1.44)	0.731	.092	(7.96)
Intercept	1.234	.244	(5.05)	0.229	.116	(1.98)	-1.006	.209	(-4.81)
β_{DOWN}	-0.766	.109	(-7.02)	0.793	.052	(15.35)	1.559	.093	(16.71)
β_{FLAT}	0.061	.074	(0.83)	1.160	.035	(33.11)	1.099	.063	(17.36)
β_{UP}	0.354	.148	(2.40)	1.293	.070	(18.48)	0.939	.126	(7.43)
s_{DOWN}	-1.775	.199	(-8.92)	0.528	.094	(5.60)	2.303	.170	(13.52)
s_{FLAT}	-0.861	.107	(-8.02)	0.978	.051	(19.26)	1.840	.092	(20.04)
s_{UP}	0.694	.193	(3.60)	1.571	.091	(17.20)	0.877	.165	(5.31)
h_{DOWN}	-0.650	.250	(-2.60)	-0.170	.118	(-1.44)	0.480	.214	(2.24)
h_{FLAT}	-0.819	.112	(-7.29)	0.058	.053	(1.08)	0.876	.096	(9.12)
h_{UP}	-0.314	.250	(-1.26)	0.196	.118	(1.66)	0.511	.213	(2.39)

Table 3. Risk-Adjusted Profitability of Total Return Momentum Strategy

For each month t, all NYSE and AMEX stocks i on the monthly CRSP tape with returns for months $t-7$ to $t-2$ are ranked according to the criterion $\sum_{\tau=t-7}^{t-2} r_{i\tau}$. The Total Return Momentum Strategy designates winners and losers as the top and bottom decile from this ranking. Portfolios are formed monthly: an equal-weighted long position in the winners and an equal-weighted short position in the losers for each investment month $t =$ August 1926 through July 1995 (828 months). Panel I shows three sets of summary statistics. The left panel shows the strategy's raw monthly profit $r_{W-L,t}$. The center panel shows the risk-adjusted profit. The right panel shows a feasible-hedged profit. The risk-adjusted and feasible-hedged profits are calculated as follows. Factor loadings are estimated from the regression $r_{W-L,\tau} = \alpha_{W-L} + \beta_{W-L}\, r_{EW\,\tau} + s_{W-L}\, OMT_\tau + e_{W-L,\tau}$. For the risk-adjusted profit, the estimation period is $\tau = t, \ldots, t+5$. The estimated factor loadings corresponding to investment month t are $\hat{\beta}_{W-L,t}$ and $\hat{s}_{W-L,t}$. The risk adjusted profit for month t is $r_{W-L,t} - \hat{\beta}_{W-L,t} r_{EW\,t} - \hat{s}_{W-L,t} OMT_t$. The feasible-hedged profit is calculated by the same method, except the estimation period is $\tau = t-61, \ldots, t-2$. Panel II uses the three-factor model for the risk adjustment and feasible hedge for each investment month $t =$ August 1966 through July 1995 (348 months). Factor loadings are estimated from the regression $r_{i\tau} = \alpha_i + \beta_i\, r_{m\tau} + s_i\, SMB_\tau + h_i\, HML_\tau + e_{i\tau}$. The risk-adjusted or feasible-hedged profit for month t is $r_{W-L,t} - \hat{\beta}_{W-L,t} r_{mt} - \hat{s}_{W-L,t} SMB_t - \hat{h}_{W-L,t} HML_t$.

	Raw Profit			Risk-Adjusted Profit			Feasible-Hedged Return		
	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan
I. Risk Adjustment with Respect to the 2-Factor Model									
				All Investment Periods 8/26-7/95					
mean (%)	0.44	-5.85	1.01	1.34	0.49	1.42	0.63	-5.30	1.16
s.d. (%)	6.90	9.86	6.27	3.19	2.76	3.22	5.35	8.13	4.68
(t-stat)	(1.83)	**(-4.93)**	**(4.44)**	**(12.11)**	(1.46)	**(12.16)**	**(3.30)**	**(-5.30)**	**(6.71)**
				8/26-8/45					
	-0.91	-5.79	-0.47	1.04	0.19	1.12	-0.25	-8.71	0.48
	10.15	12.01	9.88	4.16	2.24	4.29	8.08	10.02	7.48
	(-1.36)	**(-2.10)**	(-0.69)	**(3.80)**	(0.37)	**(3.79)**	(-0.44)	**(-3.48)**	(0.88)
				9/45-3/62					
	1.15	-3.17	1.55	1.53	0.71	1.61	1.01	-1.98	1.29
	3.19	4.64	2.70	2.47	2.44	2.47	2.74	2.27	2.61
	(5.08)	**(-2.82)**	**(7.75)**	**(8.73)**	(1.20)	**(8.78)**	**(5.20)**	**(-3.59)**	**(6.65)**
				4/62-11/78					
	0.86	-8.64	1.68	1.34	0.65	1.40	0.59	-6.66	1.22
	6.47	12.61	4.89	2.76	2.26	2.79	4.87	10.20	3.50
	(1.87)	**(-2.74)**	**(4.66)**	**(6.87)**	(1.15)	**(6.79)**	(1.70)	**(-2.61)**	**(4.72)**
				12/78-7/95					
	0.86	-5.97	1.50	1.51	0.44	1.61	1.16	-4.14	1.65
	4.97	8.07	4.07	2.95	3.97	2.84	4.15	6.70	3.47
	(2.45)	**(-3.05)**	**(4.98)**	**(7.22)**	(0.45)	**(7.67)**	**(3.95)**	**(-2.55)**	**(6.44)**
II. Risk Adjustment with Respect to the 3-Factor Model									
				All Investment Periods 8/66-7/95					
mean (%)	0.78	-7.70	1.55	1.48	1.66	1.46	0.67	-6.15	1.29
s.d. (%)	5.96	11.00	4.57	3.52	6.74	3.09	5.09	9.73	3.91
(t-stat)	**(2.45)**	**(-3.77)**	**(6.06)**	**(7.83)**	(1.33)	**(8.46)**	**(2.47)**	**(-3.41)**	**(5.91)**
				8/66-1/81					
	0.67	-8.84	1.56	1.32	1.89	1.26	0.38	-6.44	1.02
	6.75	13.09	5.03	3.70	7.48	3.17	5.52	11.69	4.05
	(1.30)	**(-2.62)**	**(3.92)**	**(4.69)**	(0.98)	**(5.03)**	(0.90)	**(-2.13)**	**(3.18)**
				2/81-7/95					
	0.89	-6.48	1.54	1.64	1.42	1.66	0.97	-5.84	1.57
	5.06	8.56	4.08	3.34	6.13	3.01	4.62	7.51	3.77
	(2.33)	**(-2.83)**	**(4.77)**	**(6.49)**	(0.86)	**(6.99)**	**(2.77)**	**(-2.91)**	**(5.26)**

Table 4. Adjusting for Cross-Sectional Variation in Expected Returns

Each month t, all NYSE and AMEX stocks i on the monthly CRSP tape with returns for months $t-7$ to $t-2$ are ranked according to the criterion $\sum_{\tau=t-7}^{t-2} r_{i\tau}$. The Total Return Momentum Strategy designates winners and losers as the top and bottom decile from this ranking. Portfolios are formed monthly: an equal-weighted long position in the winners and an equal-weighted short position in the losers for each investment month, t, August 1926 through July 1995 (828 months). The table shows three sets of summary statistics. The left panel shows the strategy's raw monthly profit $r_{W-L,t}$. The center panel shows an own-mean adjusted profit, where each winner or loser stock i's investment month t return r_{it} is adjusted by its time series mean, $\bar{r}_i$, to give $r_{it}-\bar{r}_i$. The right panel shows the result when r_{it} is adjusted by $\dot{r}_{it}$, its time series mean calculated omitting $r_{i\,t-7},\ldots,r_{i\,t-2}$, to give $r_{it}-\dot{r}_{it}$.

	Winner-Minus-Loser Raw Profits			Adjusted By Time-Series Means Over Stocks' Entire Lives			Adjusted By Time-Series Means Omitting Formation Periods		
	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan
I. Winners and Losers 1926-1995									
				All Investment Periods 8/26-7/95					
mean (%)	0.44	-5.85	1.01	-0.06	-6.40	0.51	0.46	-5.86	1.04
s.d. (%)	6.90	9.86	6.27	6.90	9.94	6.25	6.87	9.85	6.23
(t-stat)	(1.83)	**(-4.93)**	**(4.44)**	(-0.27)	**(-5.35)**	**(2.26)**	(1.94)	**(-4.94)**	**(4.59)**
				8/26-8/45					
	-0.91	-5.79	-0.47	-1.33	-6.27	-0.88	-0.85	-5.77	-0.40
	10.15	12.01	9.88	10.12	12.02	9.84	10.09	11.97	9.81
	(-1.36)	**(-2.10)**	(-0.69)	**(-1.99)**	**(-2.27)**	(-1.30)	(-1.27)	**(-2.10)**	(-0.59)
				9/45-3/62					
	1.15	-3.17	1.55	1.01	-3.31	1.41	1.17	-3.15	1.57
	3.19	4.64	2.70	3.19	4.58	2.72	3.19	4.58	2.72
	(5.08)	**(-2.82)**	**(7.75)**	**(4.45)**	**(-2.98)**	**(7.01)**	**(5.17)**	**(-2.84)**	**(7.82)**
				4/62-11/78					
	0.86	-8.64	1.68	0.38	-9.20	1.21	0.99	-8.54	1.82
	6.47	12.61	4.89	6.48	12.70	4.86	6.47	12.65	4.88
	(1.87)	**(-2.74)**	**(4.66)**	(0.83)	**(-2.90)**	**(3.38)**	**(2.17)**	**(-2.70)**	**(5.07)**
				12/78-7/95					
	0.86	-5.97	1.50	-0.13	-7.00	0.51	0.73	-6.14	1.37
	4.97	8.07	4.07	5.02	8.20	4.10	4.95	8.06	4.03
	(2.45)	**(-3.05)**	**(4.98)**	(-0.36)	**(-3.52)**	(1.69)	**(2.08)**	**(-3.14)**	**(4.59)**
II. Winners and Losers 1966-1995									
				All Investment Periods 8/66-7/95					
mean (%)	0.78	-7.70	1.55	0.03	-8.53	0.80	0.76	-7.79	1.54
s.d. (%)	5.96	11.00	4.57	5.99	11.06	4.59	5.95	10.99	4.55
(t-stat)	**(2.45)**	**(-3.77)**	**(6.06)**	(0.08)	**(-4.15)**	**(3.13)**	**(2.39)**	**(-3.82)**	**(6.04)**
				8/66-1/81					
	0.67	-8.84	1.56	0.23	-9.37	1.13	0.79	-8.80	1.70
	6.75	13.09	5.03	6.76	13.17	5.01	6.75	13.11	5.01
	(1.30)	**(-2.62)**	**(3.92)**	(0.45)	**(-2.75)**	**(2.86)**	(1.55)	**(-2.60)**	**(4.27)**
				2/81-7/95					
	0.89	-6.48	1.54	-0.18	-7.62	0.48	0.73	-6.70	1.38
	5.06	8.56	4.08	5.11	8.66	4.12	5.04	8.53	4.04
	(2.33)	**(-2.83)**	**(4.77)**	(-0.45)	**(-3.29)**	(1.46)	(1.92)	**(-2.94)**	**(4.32)**

Table 5. Real and Random Industry Momentum Strategies

Each month t, every NYSE and AMEX stock is assigned to one of twenty industry portfolios, I, which are ranked according to the criterion $\sum_{\tau=t-7}^{t-2} r_{I\tau}$, where $r_{I\tau}$ is the month τ value-weighted return on industry I. The Real Industry Momentum Strategy then designates winners and losers as the top and bottom three industries from this ranking. Portfolios are formed monthly: an equal-weighted long position in the three winner industries (with value-weighting within each industry) and an equal-weighted short position in the three loser industries (value-weighted within each industry) for each investment month $t =$ July 1963 through July 1995 (385 months). The Random Industry Momentum Strategy maintains the portfolio weights within each winner and loser industry for month t, but each stock j in a winner or loser portfolio is replaced by the stock ranking one place higher than stock j when all NYSE and AMEX stocks i are ranked according to the criterion $\sum_{\tau=t-7}^{t-2} r_{i\tau}$. Panel I shows summary statistics for both strategies, and for the monthly differences in the returns to the two strategies. The lower portion of the panel reports the results when the analysis is repeated using equal weights within industries during the investment month t. Panels II through IV conduct the same analyses as Panel I, but use different formation periods to rank the industries: Panel II uses $t-6,\ldots,t-1$; Panel III uses $t-12,\ldots,t-2$; and Panel IV uses $t-12,\ldots,t-1$.

	Real Industry Strategy			Random Industry Strategy			Real Minus Random		
	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan
I. Formation Period for month t is t-7,…,t-2									
Value Weighting									
mean (%)	0.16	-0.90	0.26	-0.01	-2.37	0.21	0.16	1.47	0.04
s.d. (%)	4.09	4.95	3.99	3.42	5.15	3.15	4.37	4.80	4.32
(t-stat)	(0.79)	(-1.03)	(1.23)	(-0.03)	(-2.61)	(1.25)	(0.73)	(1.73)	(0.19)
Equal Weighting									
	0.37	-1.24	0.52	0.07	-1.65	0.22	0.30	0.41	0.29
	3.51	4.76	3.34	1.90	2.55	1.76	3.05	3.35	3.03
	(2.09)	(-1.47)	(2.92)	(0.71)	(-3.66)	(2.40)	(1.96)	(0.69)	(1.83)
II. Formation Period for month t is t-6,…,t-1									
Value Weighting									
	0.47	-0.34	0.55	0.00	-1.31	0.12	0.47	0.98	0.43
	4.10	5.10	4.00	3.55	5.60	3.29	4.26	4.96	4.19
	(2.27)	(-0.38)	(2.57)	(0.00)	(-1.33)	(0.68)	(2.18)	(1.11)	(1.92)
Equal Weighting									
	0.78	-0.42	0.89	-0.01	-1.45	0.12	0.79	1.03	0.76
	3.54	4.86	3.38	1.79	2.52	1.66	3.03	3.60	2.98
	(4.30)	(-0.49)	(4.92)	(-0.10)	(-3.26)	(1.39)	(5.08)	(1.62)	(4.81)
III. Formation Period for month t is t-12,…,t-2									
Value Weighting									
	0.62	-0.42	0.71	0.40	-0.99	0.53	0.22	0.57	0.18
	4.09	5.04	3.99	3.33	4.55	3.18	4.09	4.34	4.08
	(2.96)	(-0.47)	(3.35)	(2.37)	(-1.23)	(3.12)	(1.03)	(0.74)	(0.85)
Equal Weighting									
	0.68	-0.43	0.78	0.28	-0.61	0.36	0.40	0.17	0.42
	3.44	4.75	3.28	1.80	3.24	1.59	2.91	3.29	2.88
	(3.89)	(-0.51)	(4.48)	(3.09)	(-1.06)	(4.30)	(2.68)	(0.30)	(2.72)
IV. Formation Period for month t is t-12,…,t-1									
Value Weighting									
	0.80	-0.21	0.89	0.25	-1.44	0.41	0.55	1.24	0.48
	4.22	5.37	4.09	3.49	5.51	3.22	4.19	5.55	4.05
	(3.71)	(-0.22)	(4.08)	(1.41)	(-1.48)	(2.37)	(2.56)	(1.26)	(2.25)
Equal Weighting									
	0.99	-0.04	1.08	0.14	-1.06	0.25	0.85	1.02	0.83
	3.57	4.75	3.44	1.90	3.04	1.72	2.92	3.11	2.91
	(5.44)	(-0.05)	(5.92)	(1.46)	(-1.96)	(2.73)	(5.69)	(1.85)	(5.38)

Table 6A. Risk Adjusted Profitability of Alternative Momentum Strategies With Respect to the 2-Factor Model: February 1929 Through July 1995

For each month t, the following two-factor model is estimated for all NYSE and AMEX stocks i on the monthly CRSP tape with returns for at least months $t-37$ to $t-2$: $r_{i\tau} = \alpha_{0i} + \alpha_{1i} D_\tau + \beta_i \, r_{EW\,\tau} + s_i \, OMT_\tau + e_{i\tau}$, $\tau = max\,\{t-61, \text{month of first observation on CRSP}\}, \ldots, t-2$; $D_\tau = 1$ if $\tau < -7$, and 0 otherwise; $r_{EW\,t}$ is the excess return on the equal-weighted market portfolio; and OMT_t is the difference in CRSP indices of returns on stocks in firm size deciles one (smallest) and ten (largest). Each strategy designates winners and losers as the top and bottom deciles according to different ranking criteria. The Total Return Momentum Strategy uses $\sum_{\tau=t-7}^{t-2} r_{i\tau}$, the Stock-Specific Return Momentum Strategy uses α_{0i}, and the Factor-Related Return Momentum Strategy uses $\sum_{\tau=t-7}^{t-2} \left(\hat{\beta}_i \, r_{EW\,\tau} + \hat{s}_i \, OMT_\tau\right)$. Portfolios are formed monthly. Each strategy enters an equal-weighted long position in the winners and an equal-weighted short position in the losers in each one month investment period $t =$ February 1929 through July 1995 (798 months). Panel I shows summary statistics for each strategy's monthly return $r_{W-L,t}$. Panel II shows the same summary statistics for each strategy after accounting for each strategy's factor risk exposure in the investment period as follows. For each winner minus loser portfolio, factor loadings are estimated from the regression $r_{W-L,\tau} = \alpha_i + \beta_{W-L} \, r_{EW\,\tau} + s_{W-L} \, OMT_\tau + e_{W-L,\tau}$, $\tau = t, \ldots, t+5$. The estimated factor loadings corresponding to investment month t are $\hat{\beta}_{W-L,t}$ and $\hat{s}_{W-L,t}$. The risk adjusted profit for month t is $r_{W-L,t} - \hat{\beta}_{W-L,t} r_{EW\,t} - \hat{s}_{W-L,t} OMT_t$.

	Total Return Momentum Strategy			Stock-Specific Return Momentum Strategy			Factor-Related Return Momentum Strategy			Total Return Strategy Excluding Stocks in Stock-Specific Strategy		
	Overall	January	Non-Jan	Overall	January	Non-Jan	Overall	January	Non-Jan	Overall	January	Non-Jan
I. Raw Profits												
							All Investment Periods 2/29-7/95					
mean (%)	0.26	-5.98	0.83	0.51	-5.39	1.04	-0.36	-2.57	-0.16	-0.34	-6.46	0.21
s.d. (%)	6.94	9.72	6.34	5.23	7.91	4.57	7.92	13.58	7.17	9.65	14.05	8.96
(t-stat)	(1.07)	**(-5.00)**	**(3.52)**	**(2.73)**	**(-5.53)**	**(6.15)**	(-1.29)	(-1.53)	(-0.62)	(-1.01)	**(-3.74)**	(0.63)
							2/29-8/45					
	-1.38	-7.28	-0.87	-0.60	-7.18	-0.03	-0.97	3.73	-1.38	-1.62	-3.88	-1.43
	10.70	12.47	10.41	7.42	9.52	6.95	12.26	19.33	11.43	14.97	15.55	14.95
	(-1.83)	**(-2.34)**	(-1.13)	(-1.15)	**(-3.02)**	(-0.06)	(-1.11)	(0.77)	(-1.63)	(-1.53)	(-1.00)	(-1.29)
							9/45-3/62					
	1.08	-3.34	1.49	0.98	-3.23	1.38	0.51	-1.69	0.72	0.79	-3.87	1.22
	3.26	4.82	2.75	3.04	3.79	2.65	3.94	5.86	3.67	4.62	6.33	4.19
	(4.66)	**(-2.85)**	**(7.30)**	**(4.56)**	**(-3.52)**	**(7.01)**	(1.83)	(-1.19)	**(2.64)**	**(2.40)**	**(-2.52)**	**(3.93)**
							4/62-11/78					
	0.80	-7.68	1.54	0.74	-6.51	1.37	0.05	-6.29	0.60	0.33	-8.07	1.06
	6.19	11.92	4.81	4.76	10.11	3.36	6.93	11.82	6.08	8.04	14.86	6.75
	(1.84)	**(-2.58)**	**(4.35)**	**(2.21)**	**(-2.58)**	**(5.54)**	(0.10)	**(-2.13)**	(1.34)	(0.58)	**(-2.17)**	**(2.13)**
							12/78-7/95					
	0.55	-5.81	1.14	0.90	-4.80	1.43	-1.04	-5.86	-0.59	-0.87	-9.97	-0.02
	5.13	8.34	4.31	4.60	7.04	3.94	6.01	12.97	4.73	7.75	17.29	5.56
	(1.51)	**(-2.87)**	**(3.58)**	**(2.76)**	**(-2.81)**	**(4.90)**	**(-2.45)**	(-1.86)	(-1.70)	(-1.58)	**(-2.38)**	(-0.06)
II. Risk Adjusted Profits												
							All Investment Periods 2/29-7/95					
mean (%)	1.21	0.21	1.30	1.41	0.49	1.50	-0.25	-0.72	-0.21	0.45	-1.02	0.58
s.d. (%)	3.24	2.50	3.29	3.11	2.60	3.14	2.71	2.89	2.69	4.97	4.64	4.99
(t-stat)	**(10.54)**	(0.69)	**(10.70)**	**(12.86)**	(1.54)	**(12.91)**	**(-2.63)**	**(-2.02)**	**(-2.11)**	**(2.53)**	(-1.78)	**(3.14)**
							2/29-8/45					
	0.97	-0.20	1.07	1.29	0.48	1.36	-0.30	-1.95	-0.15	0.13	-3.38	0.43
	4.51	2.20	4.64	4.22	2.35	4.34	3.55	2.60	3.59	6.53	5.16	6.56
	(3.04)	(-0.36)	**(3.13)**	**(4.31)**	(0.82)	**(4.24)**	(-1.18)	**(-3.00)**	(-0.57)	(0.27)	**(-2.62)**	(0.89)
							9/45-3/62					
	1.49	0.54	1.58	1.63	0.65	1.72	0.01	-0.19	0.03	0.87	-0.74	1.02
	2.53	2.43	2.53	2.53	2.06	2.56	2.34	2.00	2.37	3.44	3.37	3.42
	(8.32)	(0.92)	**(8.44)**	**(9.06)**	(1.30)	**(9.06)**	(0.07)	(-0.38)	(0.17)	**(3.57)**	(-0.90)	**(4.03)**
							4/62-11/78					
	1.19	0.55	1.25	1.35	0.56	1.42	-0.31	-0.42	-0.30	0.32	0.67	0.29
	2.63	1.97	2.68	2.59	2.37	2.60	2.17	3.05	2.09	3.48	3.22	3.51
	(6.39)	(1.12)	**(6.30)**	**(7.37)**	(0.95)	**(7.39)**	**(-2.00)**	(-0.56)	(-1.93)	(1.32)	(0.84)	(1.14)
							12/78-7/95					
	1.18	-0.06	1.30	1.40	0.29	1.50	-0.41	-0.36	-0.42	0.46	-0.66	0.57
	2.90	3.28	2.85	2.81	3.56	2.72	2.55	3.56	2.45	5.70	5.73	5.70
	(5.77)	(-0.07)	**(6.18)**	**(7.03)**	(0.33)	**(7.47)**	**(-2.29)**	(-0.42)	**(-2.31)**	(1.15)	(-0.47)	(1.35)

Table 6B. Risk Adjusted Profitability of Alternative Momentum Strategies With Respect to the 3-Factor Model: August 1966 Through July 1995

For each month t, the following three-factor model is estimated for all NYSE and AMEX stocks i on the monthly CRSP tape with returns for at least months $t-37$ to $t-2$: $r_{i\tau} = \alpha_{0i} + \alpha_{1i} D_\tau + \beta_i r_{m\tau} + s_i SMB_\tau + h_i HML_\tau + e_{i\tau}$, $\tau = max\{t-61, \text{month of first observation on CRSP}\}, \ldots, t-2$; $D_\tau = 1$ if $\tau < -7$, and 0 otherwise; r_{mt} is the excess return on the Fama-French market index; SMB_t is the size factor; and HML_t is the book-to-market factor. Each strategy designates winners and losers as the top and bottom deciles according to different ranking criteria. The Total Return Momentum Strategy uses $\sum_{\tau=t-7}^{t-2} r_{i\tau}$, the Stock-Specific Return Momentum Strategy uses α_{0i}, and the Factor-Related Return Momentum Strategy uses $\sum_{\tau=t-7}^{t-2} \left(\hat{\beta}_i r_{m,\tau} + \hat{s}_i SMB_\tau + \hat{h}_i HML_\tau\right)$. Portfolios are formed monthly. Each strategy enters an equal-weighted long position in the winners and an equal-weighted short position in the losers in each one month investment period t = August 1966 through July 1995 (348 months). Panel I shows summary statistics for each strategy's monthly raw profit $r_{W-L,t}$. Panel II shows the same summary statistics for each strategy after accounting for each strategy's factor risk exposure in the investment period as follows. For each winner minus loser portfolio, factor loadings are estimated from the regression $r_{i\tau} = \alpha_{W-L} + \beta_{W-L} r_{m\tau} + s_{W-L} SMB_\tau + h_{W-L} HML_\tau + e_{W-L,\tau}$, $\tau = t, \ldots, t+5$. The estimated factor loadings corresponding to investment month t are $\hat{\beta}_{W-L,t}$, $\hat{s}_{W-L,t}$, and $\hat{h}_{W-L,t}$. The risk-adjusted profit for month t is $r_{W-L,t} - \hat{\beta}_{W-L,t} r_{mt} - \hat{s}_{W-L,t} SMB_t - \hat{h}_{W-L,t} HML_t$.

	Total Return Momentum Strategy			Stock-Specific Return Momentum Strategy			Factor-Related Return Momentum Strategy			Total Return Strategy Excluding Stocks in Stock-Specific Strategy		
	Overall	January	Non-January	Overall	January	Non-January	Overall	January	Non-January	Overall	January	Non-January
I. Raw Profits												
							All Investment Periods 8/66-7/95					
mean (%)	0.57	-7.49	1.31	0.51	-6.77	1.17	-0.08	-2.53	0.15	0.25	-6.86	0.90
s.d. (%)	5.90	10.54	4.66	5.03	9.57	3.77	5.17	7.02	4.92	7.03	11.23	6.14
(t-stat)	(1.82)	**(-3.83)**	**(5.02)**	(1.89)	**(-3.81)**	**(5.55)**	(-0.28)	(-1.94)	(0.53)	(0.67)	**(-3.29)**	**(2.61)**
							8/66-1/81					
	0.62	-8.44	1.47	0.46	-7.25	1.19	0.10	-3.72	0.46	0.43	-8.99	1.32
	6.49	12.17	4.95	5.17	11.04	3.51	5.97	6.96	5.76	7.73	12.24	6.55
	(1.26)	**(-2.69)**	**(3.75)**	(1.18)	**(-2.54)**	**(4.28)**	(0.22)	**(-2.07)**	(1.00)	(0.73)	**(-2.84)**	**(2.53)**
							2/81-7/95					
	0.53	-6.47	1.14	0.56	-6.25	1.15	-0.25	-1.26	-0.16	0.07	-4.59	0.48
	5.25	8.83	4.35	4.90	8.09	4.04	4.24	7.11	3.91	6.26	9.97	5.70
	(1.33)	**(-2.74)**	**(3.32)**	(1.50)	**(-2.89)**	**(3.62)**	(-0.78)	(-0.67)	(-0.52)	(0.16)	(-1.72)	(1.07)
II. Risk Adjusted Profits												
							All Investment Periods 8/66-7/95					
mean (%)	1.02	-0.60	1.17	1.07	0.18	1.15	-0.16	-0.44	-0.14	0.58	-0.58	0.69
s.d. (%)	3.33	5.05	3.10	3.62	5.25	3.43	4.35	6.57	4.10	5.59	7.56	5.38
(t-stat)	**(5.74)**	(-0.63)	**(6.75)**	**(5.50)**	(0.19)	**(5.96)**	(-0.70)	(-0.36)	(-0.60)	**(1.94)**	(-0.41)	**(2.28)**
							8/66-1/81					
	0.94	-1.86	1.21	0.93	-1.26	1.14	-0.20	1.50	-0.36	0.59	0.63	0.59
	3.30	4.86	3.00	3.80	5.12	3.61	5.06	8.23	4.66	5.85	7.41	5.71
	(3.76)	(-1.48)	**(5.07)**	**(3.22)**	(-0.96)	**(3.97)**	(-0.51)	(0.71)	(-0.96)	(1.33)	(0.33)	(1.29)
							2/81-7/95					
	1.11	0.76	1.14	1.20	1.74	1.15	-0.13	-2.52	0.08	0.57	-1.87	0.79
	3.37	5.07	3.20	3.42	5.10	3.25	3.51	3.33	3.46	5.34	7.79	5.05
	(4.33)	(0.56)	**(4.50)**	**(4.63)**	(1.27)	**(4.49)**	(-0.48)	**(-2.83)**	(0.30)	(1.42)	(-0.90)	**(1.97)**

Table 7. Adjusting for Transaction Costs

Panel I reports the level of round-trip transaction cost which would remove the significance of the Total Return Momentum Strategy's raw and risk adjusted returns, and reports the level of round-trip transaction cost which would totally erase the Total Return Momentum Strategy's raw and risk adjusted returns. Panels II and III show the same figures calculated for the returns in excess of the risk-free rate on the winner portfolio only and the loser portfolio only, respectively.

	All Investment Periods 8/26-7/95						*All Investment Periods 8/66-7/95*					
	Raw Return			2-factor Risk Adjusted			Raw Return			3-factor Risk Adjusted		
	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan
I. Winner minus Loser Returns												
mean (%)	0.44	-5.85	1.01	1.34	0.49	1.42	0.78	-7.70	1.55	1.48	1.66	1.46
s.d. (%)	6.90	9.86	6.27	3.19	2.76	3.22	5.96	11.00	4.57	3.52	6.74	3.09
(t-stat)	(1.83)	(-4.93)	(4.44)	(12.11)	(1.46)	(12.16)	(2.45)	(-3.77)	(6.06)	(7.83)	(1.33)	(8.46)
Round Trip Cost which would remove significance												
%	-	-	0.74	1.48	-	1.57	0.20	-	1.38	1.46	-	1.48
Round Trip Cost which would completely dominate												
%	0.58	-	1.33	1.77	0.64	1.87	1.03	-	2.04	1.94	2.18	1.92
II. Winner Excess Return Only												
mean (%)	1.31	4.94	0.98	0.53	0.28	0.55	0.97	4.93	0.61	0.11	0.51	0.07
s.d. (%)	8.10	8.07	8.02	1.83	1.55	1.85	6.84	7.38	6.68	1.95	1.69	1.97
(t-stat)	(4.67)	(5.09)	(3.38)	(8.33)	(1.51)	(8.21)	(2.66)	(3.60)	(1.64)	(1.04)	(1.62)	(0.66)
Round Trip Cost which would remove significance												
%	2.10	8.39	1.14	1.12	-	1.16	0.70	6.21	-	-	-	-
Round Trip Cost which would completely dominate												
%	3.63	13.65	2.72	1.46	0.78	1.52	2.69	13.62	1.69	0.30	1.40	0.20
III. Loser Excess Return Only												
mean (%)	0.88	10.80	-0.03	-0.81	-0.20	-0.87	0.19	12.63	-0.94	-1.37	-1.15	-1.39
s.d. (%)	11.15	13.36	10.48	1.99	1.81	2.00	9.06	15.08	7.36	3.12	6.37	2.65
(t-stat)	(2.26)	(6.71)	(-0.07)	(-11.77)	(-0.94)	(-11.99)	(0.40)	(4.51)	(-2.28)	(-8.21)	(-0.97)	(-9.38)
Round Trip Cost which would remove significance												
%	-	-	-	1.70	-	1.82	-	-	0.33	2.61	-	2.76
Round Trip Cost which would completely dominate												
%	-	-	0.07	2.04	0.51	2.18	-	-	2.35	3.43	2.89	3.48

Figure 1. Cumulative Profits Through for the Total Return Momentum Strategy Given Alternative Dates of First Investing in the Strategy

For each month t, all NYSE and AMEX stocks i were ranked in ascending order based on $\sum_{\tau=t-7}^{t-2} r_{i\tau}$. The Total Return Momentum Strategy buys the top (winner) decile and shorts the bottom (loser) decile, holding the position for the one month investment period t. The reported cumulative profit to entering at the beginning of month t is $\sum_{\tau=t}^{\text{July1995}} r_{W-L,\tau}$, the sum of monthly gains and losses to re-entering the strategy each month with a $1 position size in both winners and losers. The first investment month t is August 1926; the last is July 1995.

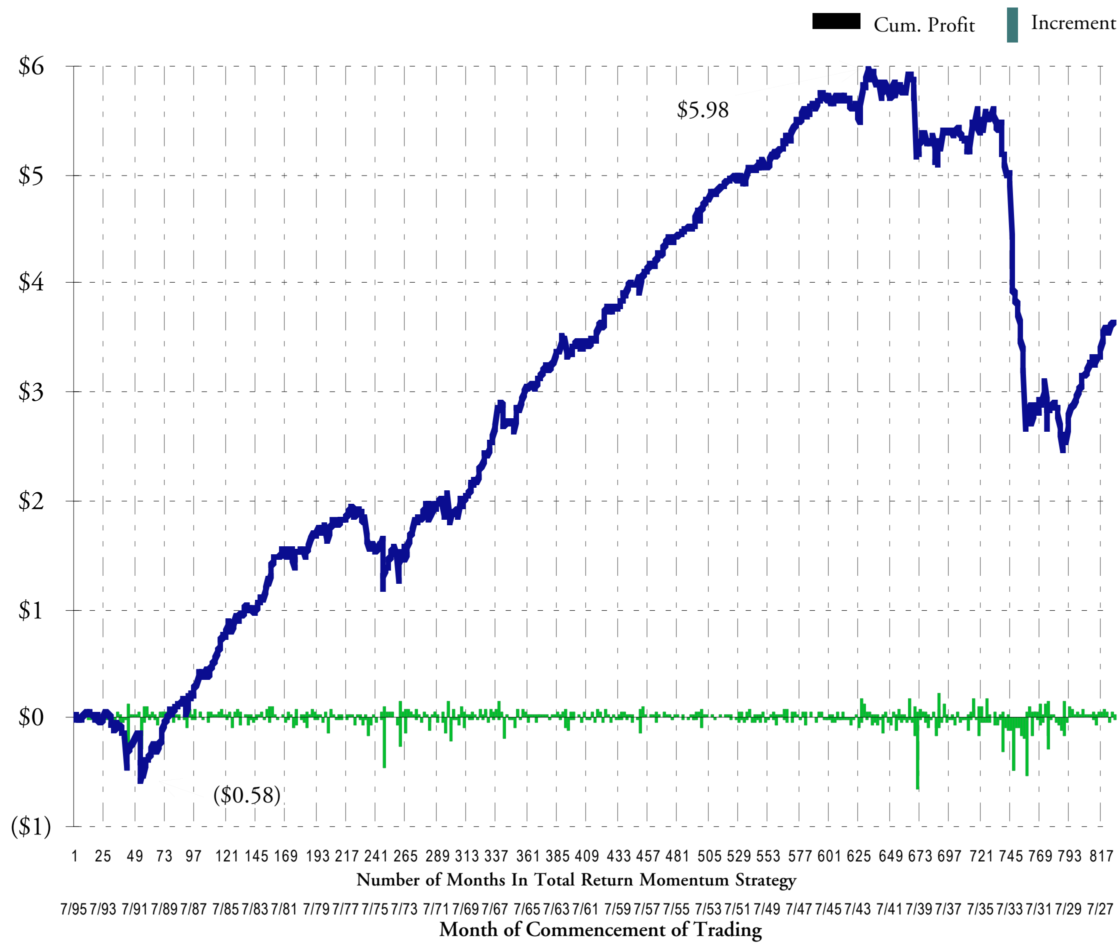


Figure 2. Monthly Performance of the Total Return Momentum Strategy

For each month t, all NYSE and AMEX stocks i were ranked in ascending order based on $\sum_{\tau=t-7}^{t-2} r_{i\tau}$. The Total Return Momentum Strategy buys the top (winner) decile and shorts the bottom (loser) decile, holding the position for the one month investment period t. The reported return is relative to a \$1 position in winners at the start of each month. The first investment month t is August 1926; the last is July 1995.

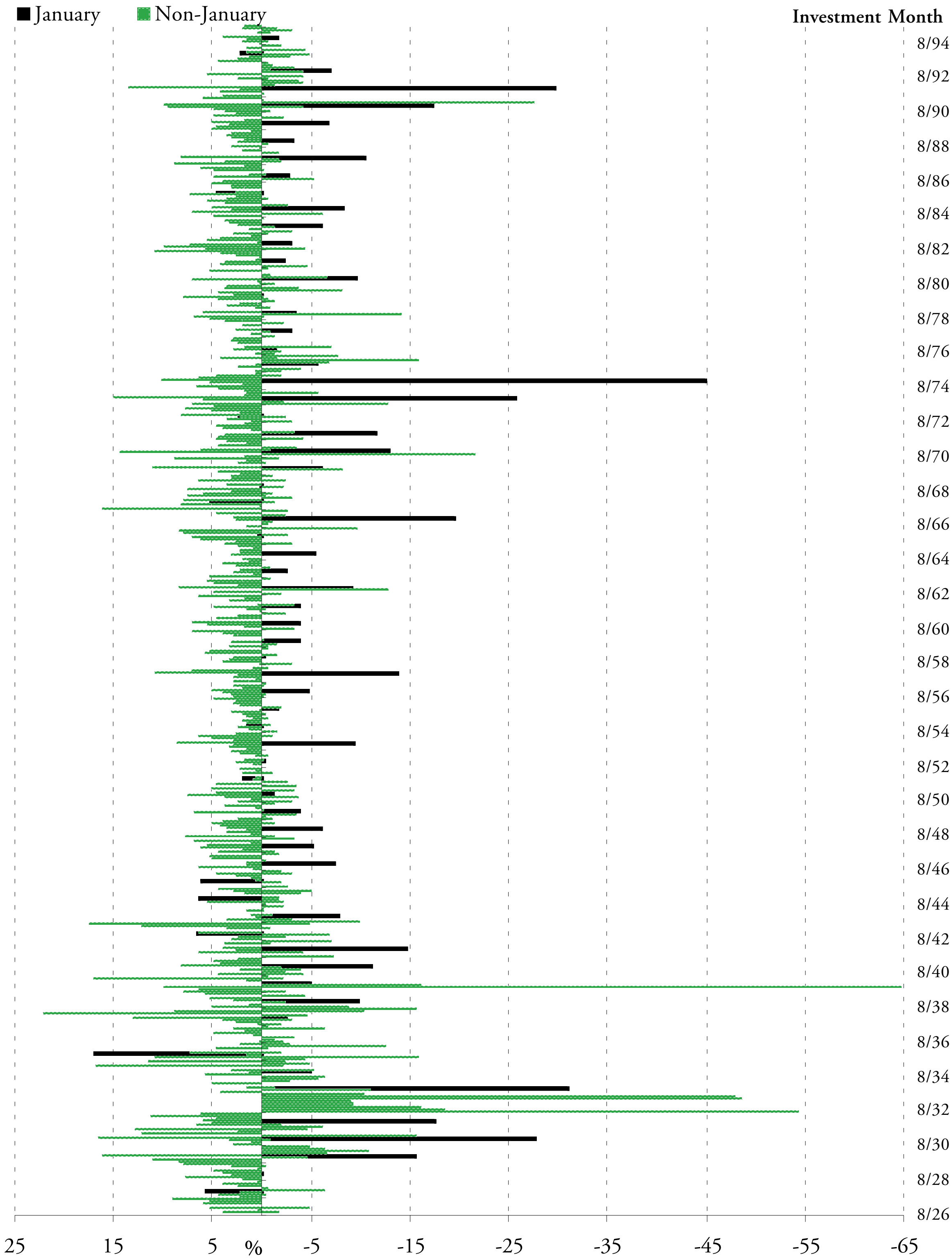


Figure 3. Winners' Beta and the Factors

Over any ranking period, the conditional expected beta of stocks in the top performance decile, $E\{\beta_W | r_{EW}, OMT\}$ is a function of the performances of both the market (r_{EW}) and size (OMT) factors over the ranking period: $E\{\beta_W | r_{EW}, OMT\} = 1 + 1.754\,\frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\sqrt{\mathcal{V}}}$, where $\mathcal{V} = \sigma_\beta^2 r_{EW}^2 + \sigma_s^2 OMT^2 + 2\,\sigma_{\beta s} r_{EW}\, OMT + \sigma_e^2$. The plot as depicted uses the parameterization $\sigma_\beta^2 = 0.133, \sigma_s^2 = 0.154, \sigma_{\beta\, s} = -0.03$, and $\sigma_e^2 = 0.066$, which are sample estimates derived from the CRSP monthly data using the methodology of Appendix B.

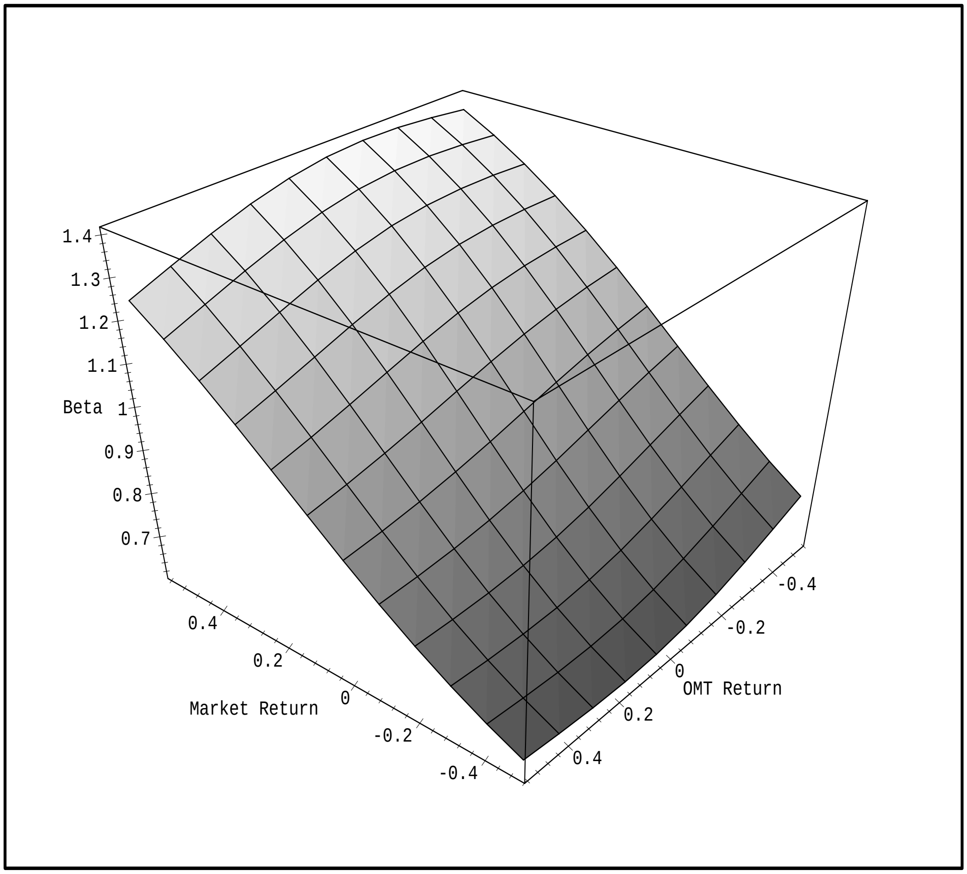


Figure 4. Stock-Specific Returns in the Winner Portfolio

Over any ranking period, the conditional expected stock-specific return of stocks in the winner decile, $E\{e_W | r_{EW}, OMT\}$, is a function of the performances of both r_{EW} and OMT over the ranking period: $E\{e_W^{\kappa} \,|\, r_{EW}, OMT\} = 1.754 \frac{\sigma_e^2}{\sqrt{\mathcal{V}}}$, where $\mathcal{V} = \sigma_\beta^2 r_{EW}^2 + \sigma_s^2 OMT^2 + 2\,\sigma_{\beta s} r_{EW}\, OMT + \sigma_e^2$. The plot as depicted uses the parameterization $\sigma_\beta^2 = 0.133$, $\sigma_s^2 = 0.154$, $\sigma_{\beta\, s} = -0.03$, and $\sigma_e^2 = 0.066$, which are sample estimates derived from the CRSP monthly data using the methodology of Appendix B.

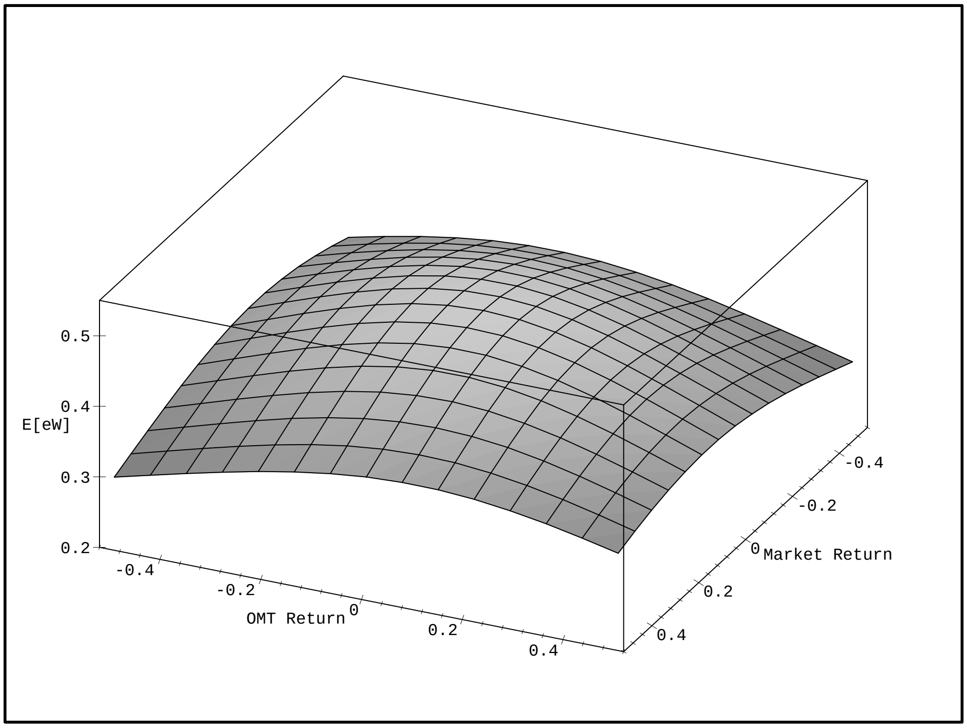
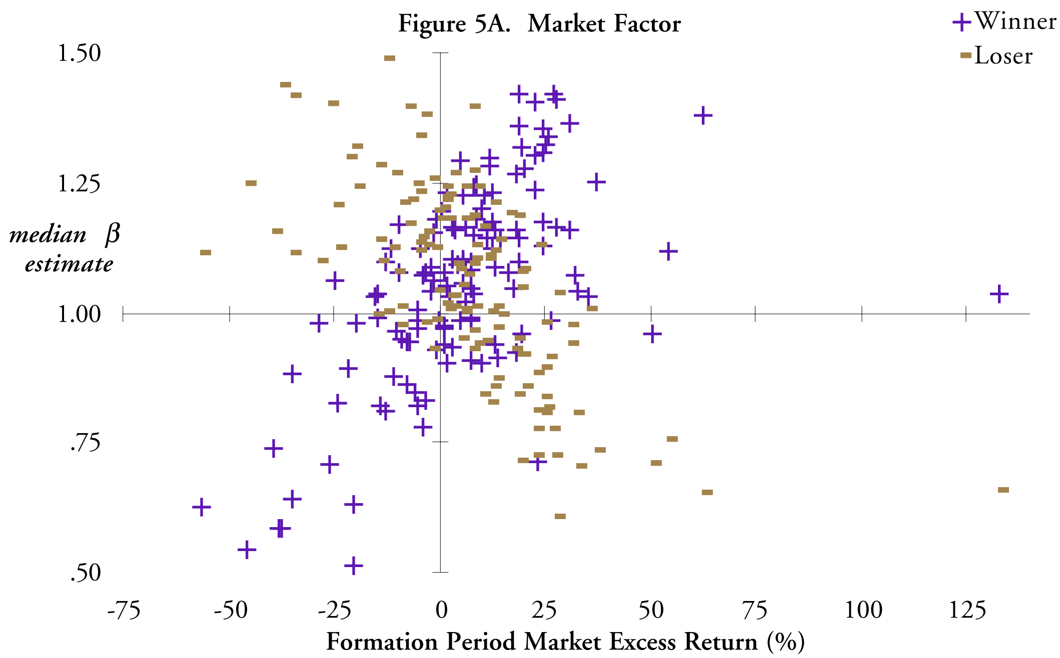


Figure 5. Formation Period Loadings of Total Return Momentum Strategy

For each winner or loser stock i which is in the month t winner or loser portfolio and which has returns for the period $\tau = t-37, \ldots, t-2$, monthly returns in excess of the riskless rate $r_{i\tau}$ are regressed on the monthly market and OMT factors: $r_{i\tau} = \alpha_i + \beta_i \, r_{EW\,\tau} + s_i \, OMT_\tau + e_{i\tau}$. The estimation period is $\tau = t-61, \ldots, t-2$; i.e., up to 60 (but at least 36) months. For each February or August t, median estimates of β_i are plotted for winners and for losers against $\sum_{\tau=t-7}^{t-2} r_{EW\,\tau}$. Also, median estimates of s_i are plotted for winners and for losers against $\sum_{\tau=t-7}^{t-2} OMT_\tau$. The first formation period is January-June 1926; the last is July-December 1994.



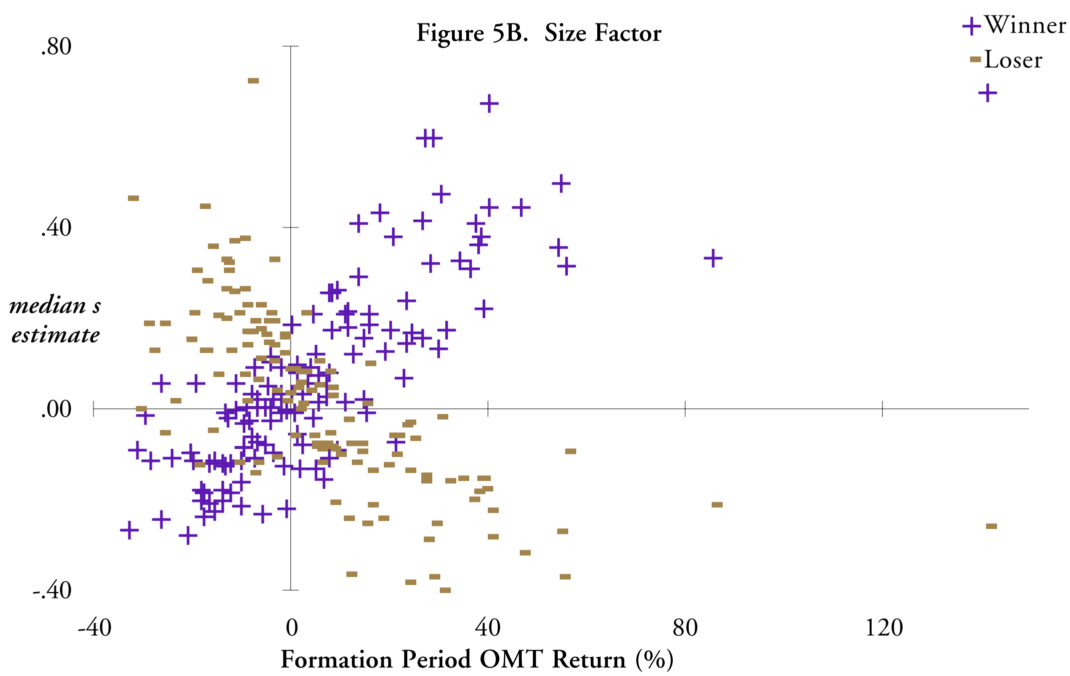
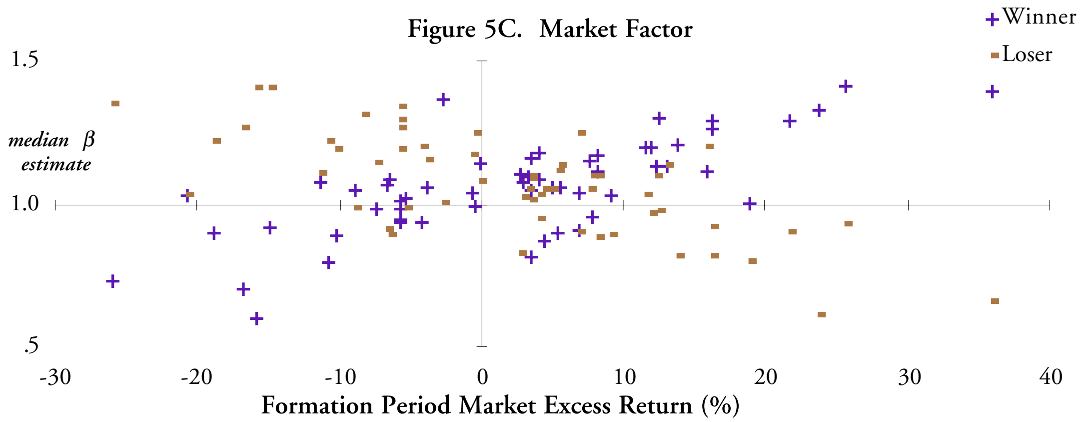
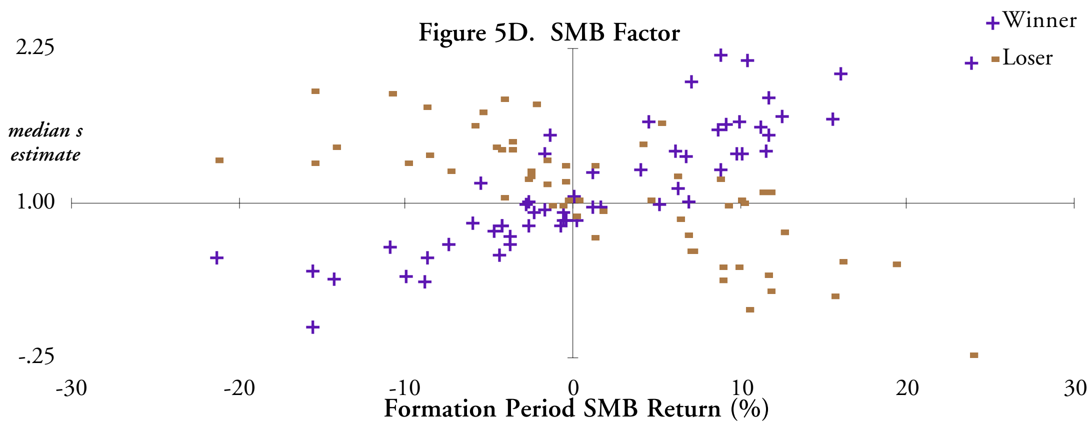


Figure 5 *continued*. Formation Period Loadings of Total Return Momentum Strategy

For each winner or loser stock i which is in the month t winner or loser portfolio and which has returns for the period $\tau = t-37, \ldots, t-2$, monthly returns in excess of the riskless rate $r_{i\tau}$ are regressed on the monthly market, SMB, and HML factors: $r_{i\tau} = \alpha_i + \beta_i \, r_{m\tau} + s_i \, SMB_\tau + h_i \, HML_\tau + e_{i\tau}$. The estimation period is $\tau = t-61, \ldots, t-2$; i.e., up to 60 (but at least 36) months. For each February or August t, median estimates of β_i are plotted for winners and for losers against $\sum_{\tau=t-7}^{t-2} r_{m\tau}$. Next, median estimates of s_i are plotted for winners and for losers against $\sum_{\tau=t-7}^{t-2} SMB_\tau$. Finally, median estimates of h_i are plotted for winners and for losers against $\sum_{\tau=t-7}^{t-2} HML_\tau$. The first formation period is January-June 1966; the last is July-December 1994.





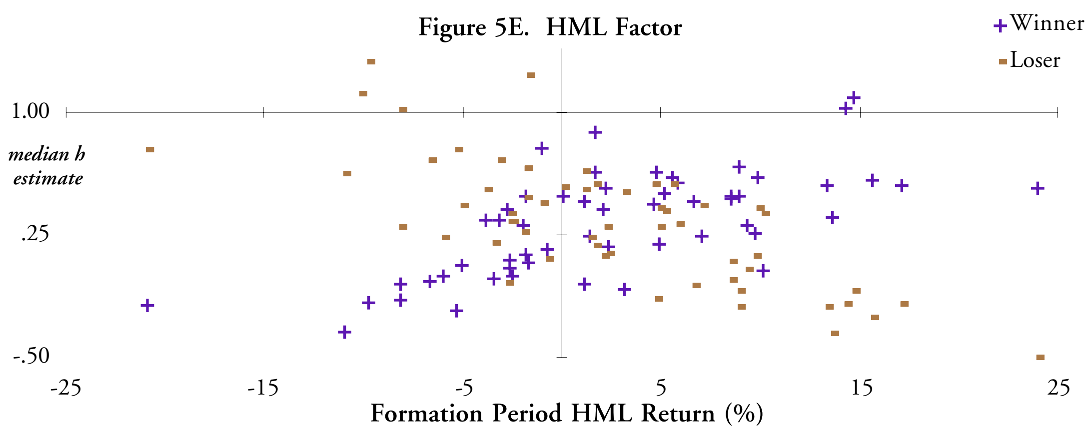
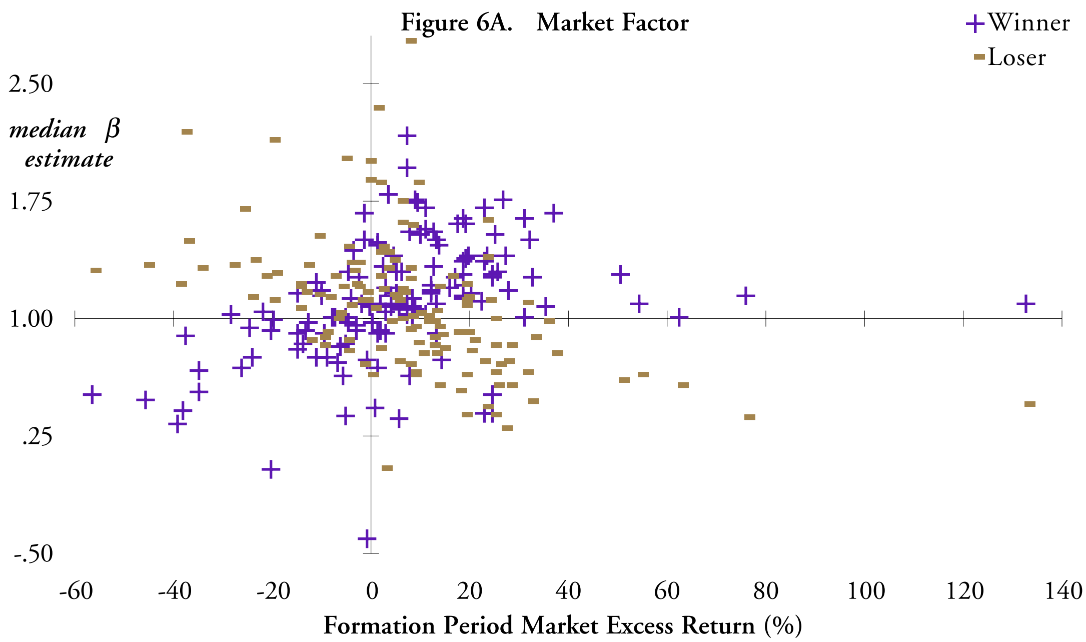


Figure 6. Investment Period Loadings of Total Return Momentum Strategy

For each winner or loser stock i in the month t winner or loser portfolio, monthly returns in excess of the riskless rate $r_{i\tau}$ are regressed on the monthly market and OMT factors: $r_{i\tau} = \alpha_i + \beta_i r_{EW\,\tau} + s_i OMT_\tau + e_{i\tau}$. The estimation period is $\tau = t, \ldots, t+5$. For each February or August t, median estimates of β_i are plotted for winners and for losers against $\sum_{\tau=t-7}^{t-2} r_{EW\,\tau}$. Also, median estimates of s_i are plotted for winners and for losers against $\sum_{\tau=t-7}^{t-2} OMT_\tau$. The first estimation period is August 1926-January 1927; the last is February-July 1995.



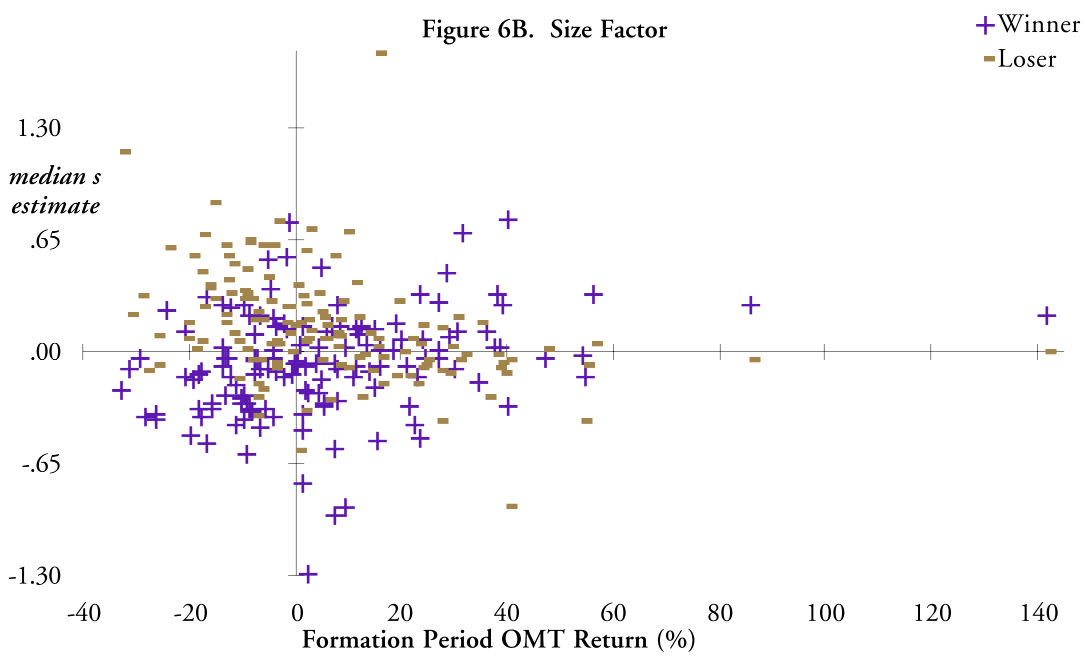


Figure 6 *continued*. Investment Loadings of Total Return Momentum Strategy

For each winner or loser stock i in the month t winner or loser portfolio, monthly returns in excess of the riskless rate $r_{i\tau}$ are regressed on the monthly market, SMB, and HML factors: $r_{i\tau} = \alpha_i + \beta_i r_{m\tau} + s_i SMB_\tau + h_i HML_\tau + e_{i\tau}$.The estimation period is $\tau = t, \ldots, t+5$. For each February or August t, Figure 6C plots median estimates of β_i for winners and for losers against $\sum_{\tau=t-7}^{t-2} r_{m\tau}$. Figure 6D plots median estimates of s_i for winners and for losers against $\sum_{\tau=t-7}^{t-2} SMB_\tau$. Figure 6E plots median estimates of h_i for winners and for losers against $\sum_{\tau=t-7}^{t-2} HML_\tau$. The first estimation period is August 1966-January 1967; the last is February-July 1995.

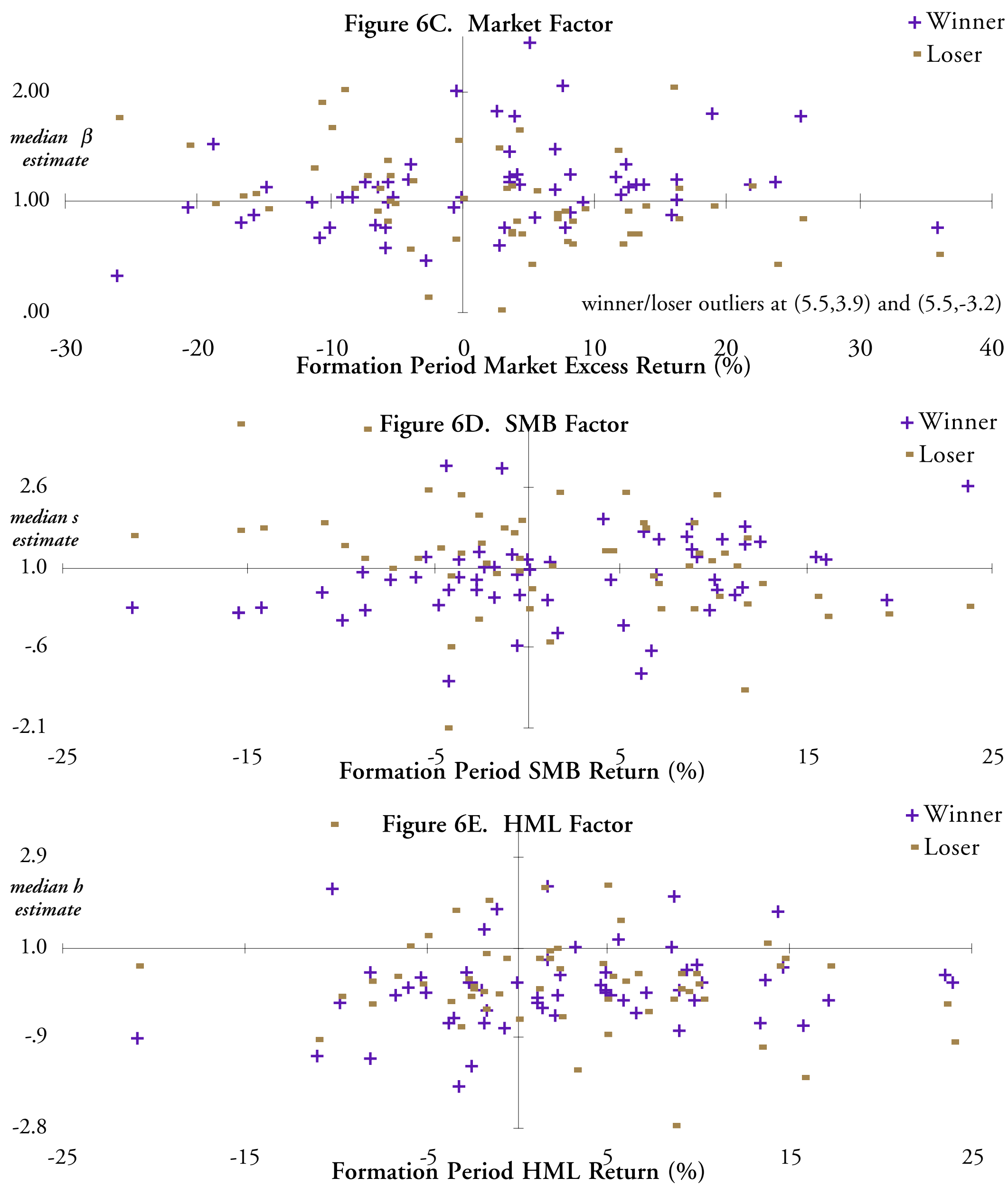


Figure 7. Risk Adjusted Performance of the Total Return Momentum Strategy

For each month t, all NYSE and AMEX stocks i are ranked in ascending order based on $\sum_{\tau=t-7}^{t-2} r_{i\tau}$. The Total Return Momentum Strategy buys the top (winner) decile and shorts the bottom (loser) decile, holding the position for the one month investment period t. The first investment month is August 1926; the last is July 1995. Winner minus loser returns are plotted after accounting for the strategy's factor risk exposure in the investment period as follows. Factor loadings are estimated from the regression $r_{W-L,\tau} = \alpha_{W-L} + \beta_{W-L}\, r_{EW,\tau} + s_{W-L}\, OMT_\tau + e_{W-L,\tau}$, $\tau = t, \ldots, t+5$. The estimated factor corresponding to investment month t are $\hat{\beta}_{W-L,t}$ and $\hat{s}_{W-L,t}$. The risk adjusted profit for month t is $r_{W-L,t} - \hat{\beta}_{W-L,t} r_{EW,t} - \hat{s}_{W-L,t} OMT_t$.

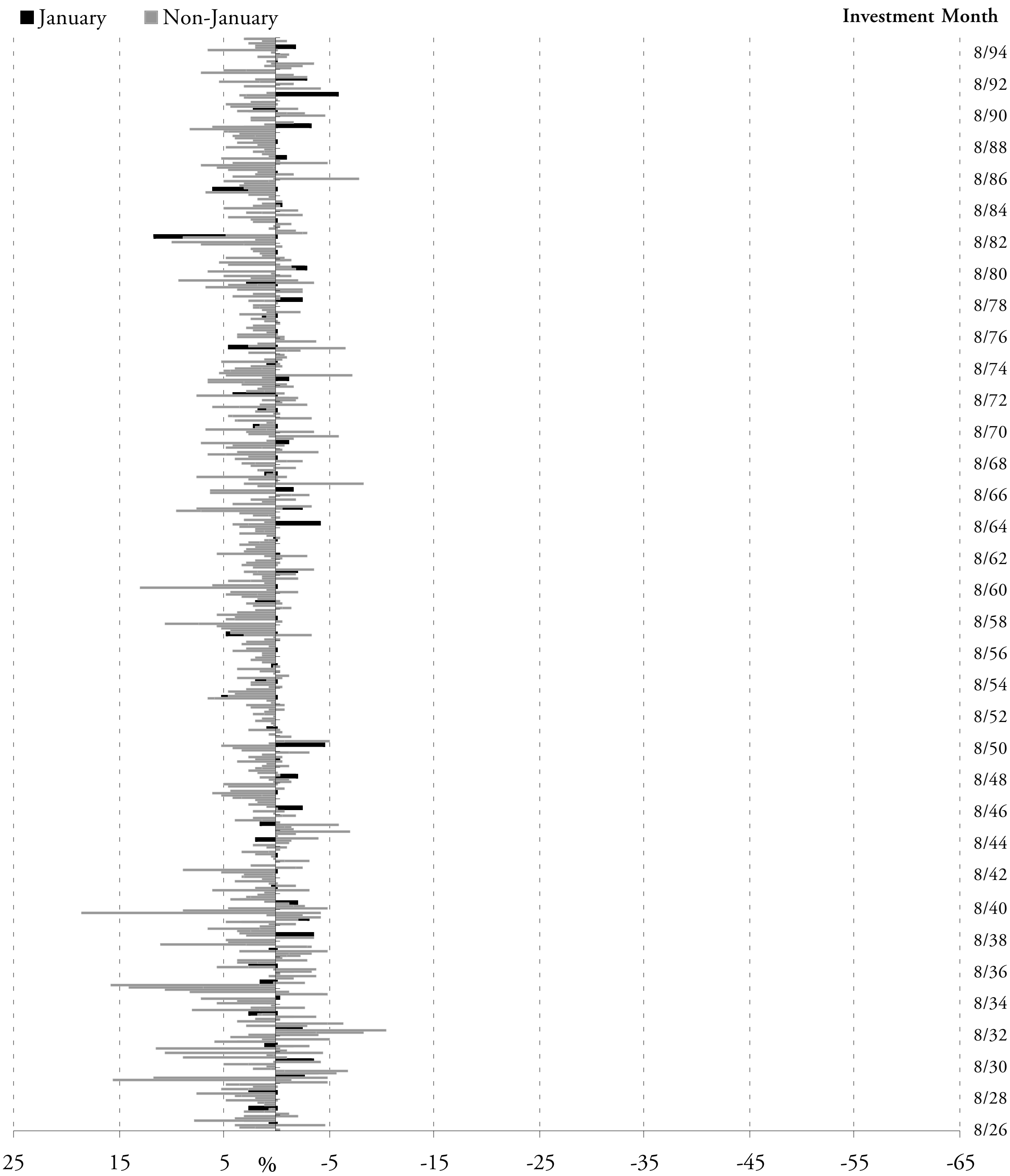


Figure 8. January Profits and the Size Factor

For each stock i in the month t winner or loser investment portfolio, monthly returns in excess of the riskless rate $r_{i\tau}$ are regressed on the monthly market and OMT factors: $r_{i\tau} = \alpha_i + \beta_i r_{EW\,\tau} + s_i OMT_\tau + e_{i\tau}, \tau = t, \ldots, t+5$. Mean estimates of winner minus loser s_i, $\hat{s}_{W-L,t}$, are then used to calculate the OMT-related profit for each January t as $\hat{s}_{W-L,t} OMT_t$. The OMT-related profit is then plotted against total January profit $r_{W-L,t}$.

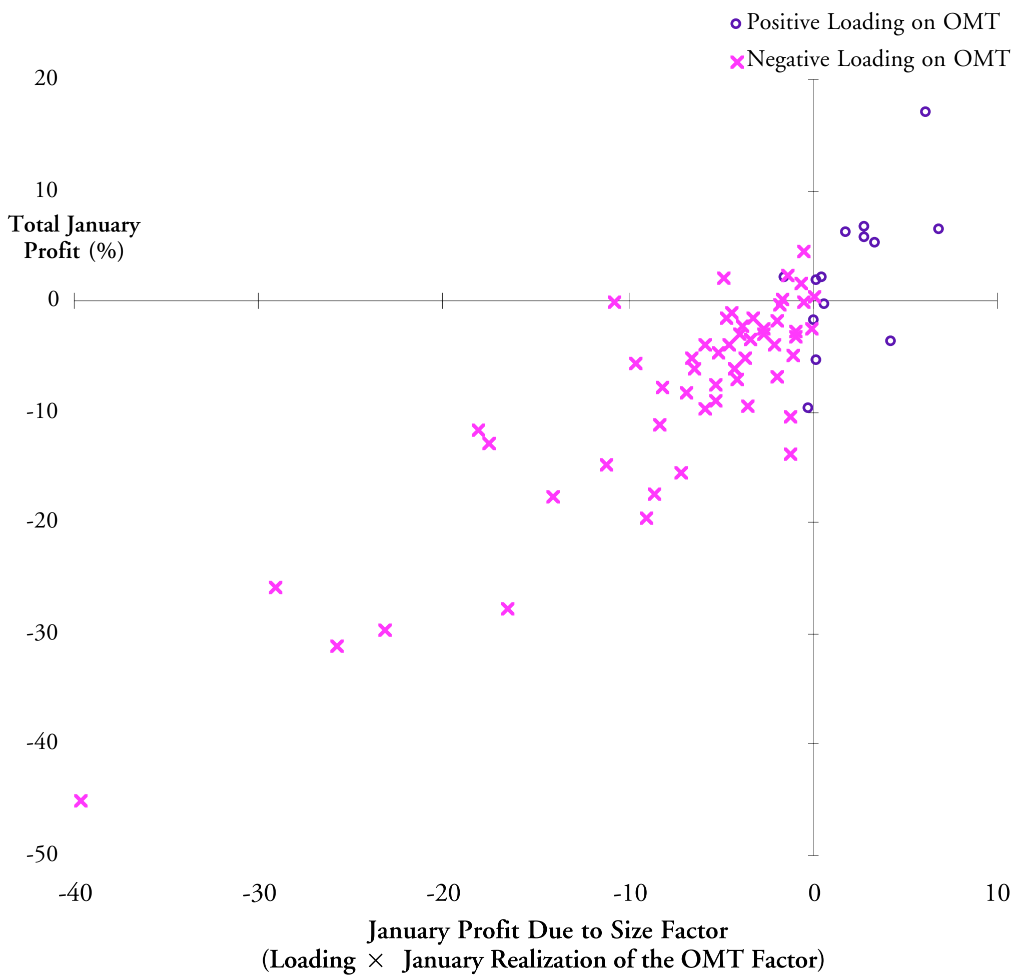
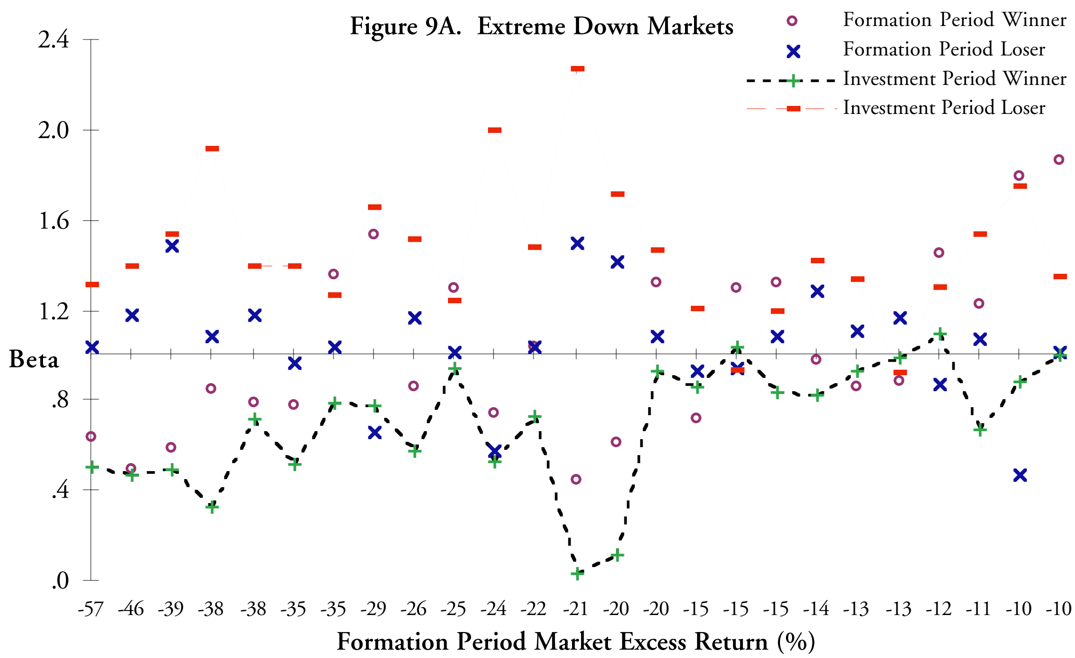
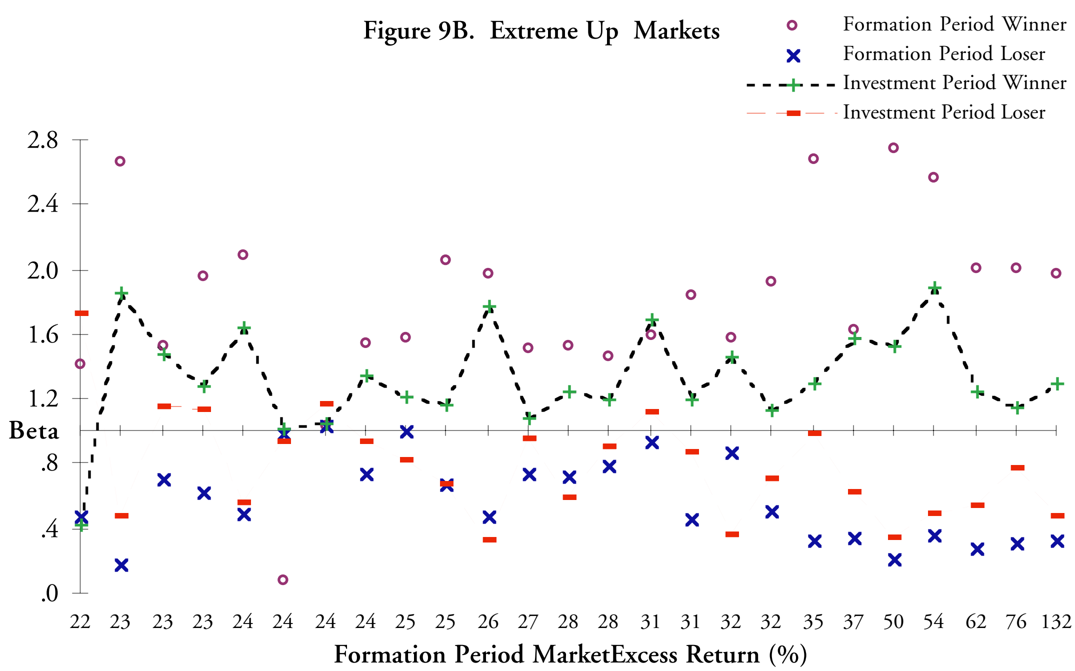


Figure 9. Formation and Investment Period Winner and Loser 1-Factor Betas

For each stock i in the month t winner or loser investment portfolio, monthly returns in excess of the riskless rate $r_{i\tau}$ are regressed on the monthly market factor: $r_{i\tau} = \alpha_i + \beta_i\, r_{EW\,\tau} + e_{i\tau}$. For each formation period estimate, $\tau = t-7, \ldots, t-2$; for each investment period estimate, $\tau = t, \ldots, t+5$. Median estimates are plotted for the February or August t with the 25 most extreme realizations of $\sum_{\tau=t-7}^{t-2} r_{EW\,\tau}$.





Appendix A

Suppose that returns over a given period are given by a factor model of the form:

$$
\begin{aligned}
r_i &= \beta_i r_{EW} + s_i OMT + e_{it}. \\
e_i &\sim i.i.d.N(0, \sigma_e^2). \\
\begin{pmatrix} \beta_i \\ s_i \end{pmatrix} &\sim N\left(\begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\beta^2 & \sigma_{\beta s} \\ \sigma_{\beta s} & \sigma_s^2 \end{pmatrix} \right).
\end{aligned}
$$

Note that β_i and s_i are *marginal* betas and size loadings. The conditional cross-sectional distribution of the r_i is $N(r_{EW}, \mathcal{V})$, where

$$\mathcal{V} := \sigma_\beta^2 {r^2}_{EW} + \sigma_s^2 (OMT)^2 + 2\sigma_{\beta s} r_{EW} OMT + \sigma_e^2.$$

Conditional on r_{EW} and OMT, stocks' excess returns and betas have a bivariate normal distribution:

$$\beta_i = \frac{\sigma_s^2 OMT + \sigma_{\beta s} r_{EW} OMT + \sigma_e^2}{\mathcal{V}} + \frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\mathcal{V}} r_i + \omega, \qquad (A1')$$

where ω has a mean 0 Normal distribution and is independent of r_i. Hence:

$$E\{\beta_i \,|\, r_{EW}, OMT, r_i\} = \frac{\sigma_s^2 OMT + \sigma_{\beta s} r_{EW} OMT + \sigma_e^2}{\mathcal{V}} + \frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\mathcal{V}} r_i \,. \qquad (A1'')$$

Let $\Phi(x)$ denote the area under a standard normal density to the left of x. Define $Z(x)$ as $Z(x) \equiv \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$. Given the assumed multivariate Normality, the top $\kappa \times 100\%$ of firms in the population will have realized returns exceeding the population mean return, r_{EW}, by at least $\Phi^{-1}(1-\kappa)$ standard deviations. Thus, the top $\kappa \times 100\%$ of firms will have realized returns exceeding $r_{EW} + \Phi^{-1}(1-\kappa)\sqrt{\mathcal{V}}$.

Let $E\{\beta_W^\kappa \,|\, r_{EW}, OMT\}$ denote the conditional expected beta of stocks in the winner $\kappa \times 100\%$ quantile:

$$E\{\beta_W^\kappa \,|\, r_{EW}, OMT\} := E\left\{\beta_i \,|\, r_{EW}, OMT\,,\, r_i > r_{EW} + \Phi^{-1}(1-\kappa)\sqrt{\mathcal{V}}\right\}.$$

For $Y \sim N(\xi, \sigma^2)$, the expectation of a truncation of the distribution of Y is (Johnson and Kotz (1970, pp. 81):

$$E\{Y \,|\, Y > \theta\} = \xi + \frac{Z\left(\frac{\theta - \xi}{\sigma}\right)}{1 - \Phi\left(\frac{\theta - \xi}{\sigma}\right)} \sigma. \qquad (A2)$$

Combining $(A1'')$ and $(A2)$ gives:

$$\begin{aligned}
E\{\beta_W^\kappa \,|\, r_{EW}, OMT\} &= \frac{\sigma_s^2 OMT + \sigma_{\beta s} r_{EW} OMT + \sigma_e^2}{\mathcal{V}} + \frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\mathcal{V}} \times \\
&\quad E\left\{ r_i \,|\, r_{EW}, OMT\,,\, r_i > r_{EW} + \Phi^{-1}(1-\kappa)\sqrt{\mathcal{V}} \right\} \\
&= \frac{\sigma_s^2 OMT + \sigma_{\beta s} r_{EW} OMT + \sigma_e^2}{\mathcal{V}} + \frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\mathcal{V}} \times \\
&\quad \left(r_{EW} + \frac{Z\left(\frac{r_{EW} + \Phi^{-1}(1-\kappa)\sqrt{\mathcal{V}} - r_{EW}}{\sqrt{\mathcal{V}}}\right)}{1 - \Phi\left(\frac{r_{EW} + \Phi^{-1}(1-\kappa)\sqrt{\mathcal{V}} - r_{EW}}{\sqrt{\mathcal{V}}}\right)} \sqrt{\mathcal{V}} \right) \\
&= 1 + \frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa} \frac{\sigma_\beta^2 r_{EW} + \sigma_{\beta s} OMT}{\sqrt{\sigma_\beta^2 r^2{}_{EW} + \sigma_s^2 r^2{}_{OMT} + 2\sigma_{\beta s} r_{EW} OMT + \sigma_e^2}} \,.
\end{aligned}$$

$$\begin{aligned}
\frac{\partial E\{\beta_W^\kappa \,|\, r_{EW}, OMT\}}{\partial r_{EW}} &= \frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa} \frac{\sigma_\beta^2 \sigma_s^2 (OMT)^2 \left(1 - \rho_{\beta s}^2\right) + \sigma_\beta^2 \sigma_e^2}{\mathcal{V}^{3/2}} > 0. \\
\frac{\partial E\{\beta_W^\kappa \,|\, r_{EW}, OMT\}}{\partial OMT} &= \frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa} \frac{\sigma_\beta^2 \sigma_s^2 r_{EW} OMT \left(\rho_{\beta s}^2 - 1\right) + \sigma_{\beta s} \sigma_e^2}{\mathcal{V}^{3/2}}. \qquad (A3)
\end{aligned}$$

From $(A3)$ it can be seen that the sign of $\frac{\partial E\{\beta_W^\kappa \,|\, r_{EW}, OMT\}}{\partial OMT}$ is quite complex.

$$\frac{E\{\beta_W^\kappa \,|\, r_{EW}, OMT\}}{\partial OMT} \begin{cases} < 0: & \text{if } r_{EW} OMT > \frac{\rho_{\beta s}\sigma_e^2}{\sigma_\beta \sigma_s \left(1 - \rho_{\beta s}^2\right)}; \\ = 0: & \text{if } r_{EW} OMT = \frac{\rho_{\beta s}\sigma_e^2}{\sigma_\beta \sigma_s \left(1 - \rho_{\beta s}^2\right)}; \\ > 0: & \text{otherwise.} \end{cases}$$

A sufficient condition for $\frac{\partial E\{\beta_W^\kappa \,|\, r_{EW}, OMT\}}{\partial OMT}$ to be negative for all values of $r_{EW} OMT > 0$ is $\rho_{\beta s} < 0$.

Conditional on r_{EW} and OMT, excess stock returns and their idiosyncratic component have a bivariate normal distribution with

$$E\{e_i \,|\, r_i\} = \frac{\sigma_e^2}{\mathcal{V}} \left(r_i - r_{EW}\right) \,. \qquad (A4)$$

From $(A2)$ we have:

$$E\{e_W^\kappa\} = \frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa} \sigma_e \,.$$

Combining $(A4)$ and $(A2)$ gives:

$$E\{e_W^\kappa \,|\, r_{EW}, OMT\} = \frac{\sigma_e^2}{\mathcal{V}} E\left\{ r_i \,|\, r_{EW}, OMT\,,\, r_i > r_{EW} + \Phi^{-1}(1-\kappa)\sqrt{\mathcal{V}} \right\} = \frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa} \frac{\sigma_e^2}{\sqrt{\mathcal{V}}} \,.$$

Appendix B

What is the sign of $\rho_{\beta s}$? For each of the 14 non-overlapping 60 month periods between 1/26 and 12/95, we estimate the marginal beta and size loadings of every NYSE- and AMEX-listed stock contained on the CRSP monthly tape over at least 36 of the 60 months. We assume that the β_i and s_i values are constant within each five year window, but may change between windows. Hence we use the notation $\beta_{i\mathcal{T}}$ and $s_{i\mathcal{T}}$ to denote stock i's factor loadings in the 60 month period ended in month $\mathcal{T}$. Let $\hat{\beta}_{i\mathcal{T}}$ and $\hat{s}_{i\mathcal{T}}$ denote the corresponding 60 month regression estimates.

$$\begin{aligned} \hat{\beta}_{i\mathcal{T}} &= \beta_{i\mathcal{T}} + \hat{\varepsilon}^{\beta}_{i,\mathcal{T}}. \\ \hat{s}_{i\mathcal{T}} &= s_{i\mathcal{T}} + \hat{\varepsilon}^{s}_{i,\mathcal{T}}. \end{aligned}$$

It is straightforward to calculate the cross-sectional correlation of $\hat{\beta}_{i\mathcal{T}}$ and $\hat{s}_{i\mathcal{T}}$ for each $\mathcal{T}$. All 14 estimates are negative. Their average is -0.31.

But this is a biased estimate of the cross-correlation of the true factor loadings. For each stock i in a given estimation period ending in month $\mathcal{T}$, $\hat{\varepsilon}^{\beta}_{i,\mathcal{T}}$ is not independent of $\hat{\varepsilon}^{s}_{i,\mathcal{T}}$. We therefore estimate $\rho_{\beta s}$ by recognizing that

$$\rho_{\beta s} = \frac{cov(\beta, s)}{\sigma(\beta)\sigma(s)} \tag{B1}$$

and forming unbiased estimates of $cov(\beta, s)$, $\sigma(\beta)$ and $\sigma(s_i)$. First consider estimating $cov(\beta, s)$. For each 60 month estimation period we have, after dropping the subscript $\mathcal{T}$ for notational ease,

$$\text{cross-sectional } cov\left(\hat{\beta}_i, \hat{s}_i\right) = \text{cross-sectional } cov\left(\beta_i, s_i\right) + \text{cross-sectional } cov\left(\hat{\varepsilon}^{\beta}_i, \hat{\varepsilon}^{s}_i\right). \tag{B2}$$

The left-hand-side of ($B2$) is straightforward to calculate. We estimate the first term on the right-hand-side ($B2$) by subtracting from our estimate of the cross-sectional $cov\left(\hat{\beta}_i, \hat{s}_i\right)$ an estimate of the cross-sectional $cov\left(\hat{\varepsilon}^{\beta}_i, \hat{\varepsilon}^{s}_i\right)$.

We obtain an estimate of the cross-sectional $cov\left(\hat{\varepsilon}^{\beta}_i, \hat{\varepsilon}^{s}_i\right)$ by recognizing that, if $\sigma^2_{e_i} = \sigma^2_e$ for all i in relation (2), then the expectation of the cross-sectional $cov\left(\hat{\varepsilon}^{\beta}_i, \hat{\varepsilon}^{s}_i\right)$ is simply equal to the covariance between the errors in the estimates of any stock's market and size factor loadings. The covariance between these sample estimates is σ^2_e times the upper-right element of the inverse of the 60 month sample variance-covariance matrix of the factor realizations. Thus we estimate the cross-sectional $cov\left(\hat{\varepsilon}^{\beta}_i, \hat{\varepsilon}^{s}_i\right)$

as the product of this upper-right element and the average across all stocks of the sample estimates of $\sigma^2_{e_i}$ obtained from the regressions used to estimate the factor loadings. We calculate 14 separate estimates of the cross-sectional $cov(\beta_i, s_i)$, one for each non-overlapping 60 month window in which the individual stock's factor loadings are assumed constant.

Using the same logic we obtain 14 corresponding estimates of the cross-sectional $\sigma^2(\beta_i)$ and the cross-sectional $\sigma^2(s_i)$. The final 14 estimates of the cross-sectional correlation between the market and size factor loadings are obtained by substituting in $(B1)$ each set of estimates of the cross-sectional $cov(\beta_i, s_i)$, cross-sectional $\sigma(\beta_i)$ and cross-sectional $\sigma(s_i)$. The average of these 14 estimates is -0.187, with an associated t-statistic of -3.9.

Appendix C

Suppose that the residuals from a posited asset pricing model are, cross-sectionally, conditionally independent and satisfy:

$$e_{i,t} = \rho_t e_{i,t-1} + w_{i,t}\ ,$$

with $w_{i,t} \sim i.i.d.\, N(0, \sigma^2_{w_t})$. If $\rho_t > 0$ for all t, then a momentum strategy will be profitable.

The first example of, cross-sectionally, conditionally independent autocorrelated residuals being explained by a factor model occurs when $\rho_t \neq \rho$ for all t, but $\sigma^2_{w,t} = \sigma^2_w$ (and hence $\sigma^2_{e,t} = \sigma^2_e$) for all t. Take as a factor the difference in month t stock-specific returns between the stocks in the top and bottom deciles of one month lagged stock-specific return performance.

$$f_t := e^{0.1}_{W-L,t}\,.$$

The exponent is simply the parameter κ of Appendix A corresponding to the top and bottom deciles. Given a large population of stocks:

$$\begin{aligned} f_t &\approx \rho_t\, e^{0.1}_{W-L,t-1} \\ &\approx \rho_t\, 2\frac{Z\left(\Phi^{-1}(1-0.1)\right)}{.1}\sigma_e\,. \end{aligned}$$

The loadings of individual stocks on this time-varying factor will not be constant: no stock will consistently enjoy a positive or negative stock-specific return. But one can construct portfolios with constant factor loadings. Consider a portfolio containing the stocks in the $\kappa\,100$ percentile of lagged stock-specific return performance. Let $e_{\kappa,t}$ denote the month t stock-specific return on this portfolio.

$$\begin{aligned} e_{\kappa,t} &= \rho_t\, e_{\kappa,t-1} \\ &\approx \rho_t\, \frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa} \sigma_e\,. \end{aligned}$$

The common variation through time in both the factor and the stock-specific return on the portfolio reflects the changing strength of the autocorrelation in stock-specific returns through time. For an infinitely large population of stocks:

$$e_{\kappa,t} = \frac{1}{2}\, \frac{\frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa}}{\frac{Z\left(\Phi^{-1}(1-0.1)\right)}{.1}}\, f_t\,.$$

This portfolio will have a constant weight, $\frac{Z\left(\Phi^{-1}(1-\kappa)\right)}{\kappa}\Big/ 2\frac{Z\left(\Phi^{-1}(1-0.1)\right)}{.1}$, on the momentum factor. The factor f_t will completely 'explain' differences in returns on portfolios formed on the basis of lagged stock-specific returns.

The second example of, cross-sectionally, conditionally independent autocorrelated residuals being explained by a factor model occurs when $\sigma^2_{w,t} \neq \sigma^2_w$ (and hence $\sigma^2_{e,t} \neq \sigma_e$) for all t, but $\rho_t = \rho$ for all t. Again, take as a factor the difference in month t stock-specific returns between the stocks in the top and bottom deciles of one month lagged stock-specific return performance. The factor will be large following months in which the cross-sectional dispersion of stock-specific returns was large. Again the portfolio of stocks in the $\kappa \times 100$ percentile of lagged stock-specific return performance will have constant loadings on the factor. The variation through time in both the factor and the stock-specific return on the portfolio will reflect the changing lagged variance of stock-specific returns and, again, the factor will 'explain' differences in returns on portfolios formed on the basis of lagged stock-specific returns.

References

Asness, Clifford S., 1995 The power of past stock returns to explain future stock returns, Unpublished working paper (Goldman Sachs Asset Management, New York, NY).

Barberis, Nicholas, Andrei Shleifer and Robert W. Vishny, 1997, A model of investor sentiment, NBER working paper 5926.

Bernard, Victor L., 1992, Stock price reactions to earnings announcements, in Richard Thaler ed., Advances in Behavioral Finance (Russel Sage Foundation, New York NY).

Carhart, Mark M., 1977, On persistence in mutual fund performance, Journal of Finance 52(1), 57–82.

Chan, K.C., 1988, On the contrarian investment strategy, Journal of Business 61(2), 147–163.

Chan, Louis K.C., Narasimham Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, Journal of Finance 51(5), 1681–1714.

Conrad, Jennifer and Gautum Kaul, 1997, An anatomy of trading strategies, Review of Financial Studies, forthcoming.

Cooper, Michael, Roberto C. Gutierrez, Jr., and Bill Marcum, 1996, Is predictability simply hindsight?, Unpublished working paper (University of North Carolina, Chapel Hill NC).

Daniel, Kent, David Hirshleifer and Avanidhar Subrahmanyam, 1997, A theory of overconfidence, self-attribution, and security market under- and over-reactions, Unpublished working paper (Northwestern University, Evanston IL).

Daniel, Kent and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, Journal of Finance 52(1), 1–34.

DeBondt, Werner F.M. and Richard Thaler, 1985, Does the stock market overreact?, Journal of Finance 40(3), 793–805.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, Journal of Finance 51(1), 55–84.

Grinblatt, Mark, Sheridan Titman and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, American Economic Review 85(5), 1088–1105.

Hong, Harrison, and Jeremy C. Stein, 1997, A unified theory of underreaction, momentum trading and overreaction in asset markets, Unpublished working paper (MIT, Cambridge MA).

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional CAPM and the cross-section of expected returns, Journal of Finance 51(1), 3–53.

Jegadeesh, Narasimhan, 1990, “Evidence of predictable behavior of security returns,” Journal of Finance 45(3), 881–898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for market efficiency, Journal of Finance 48(1), 65–91.

Jegadeesh, Narasimhan, and Sheridan Titman, 1995, Overreaction, delayed reaction, and contrarian profits, Review of Financial Studies 8(4), 973–993.

Johnson, Norman L., and Samuel Kotz, 1970, Distributions in Statistics: Continuous Univariate Distributions–1 (Wiley, New York N.Y.).

Keim, Donald B., and Ananth Madhavan, 1997, Transactions costs and investment style: an interexchange analysis of institutional equity trades, Journal of Financial Economics 46(3), 265–292.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, Journal of Finance 51(5), 1715–1742.

Lehmann, Bruce, 1990, “Fads, martingales and market efficiency,” Quarterly Journal of Economics 105(1), 1–28.

Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, Review of Financial Studies 3(2), 175–205.

Reinganum, Marc R., 1983, The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects, Journal of Financial Economics 12(1), 89–104.

Rouwenhorst, K. Geert, 1998, International momentum strategies, Journal of Finance 53(1), 267–284.

Shumway, Tyler, 1997, The delisting bias in CRSP Data, Journal of Finance 52(1), 327–340.

Shleifer, Andrei and Robert W. Vishny, 1997, The limits of arbitrage, Journal of Fiannce 52(1), 35–55.

Wermers, Russ, 1997, Momentum investment strategies of mutual funds, performance persistence, and survivorship bias, Unpublished working paper (University of Colorado, Boulder CO).