Momentum profits and the autocorrelation of stock returns

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Abstract

This paper investigates the autocorrelation patterns in stock returns to better understand the source of momentum profits. The autocorrelations provide no evidence that investors underreact to new information. Over intermediate horizons of one to 18 months, higher past returns for stock portfolios are almost always associated with lower future returns during the period 1941 – 1997. Cross-serial correlations among stocks are also negative and, using the framework of Lo and MacKinlay (1990), appear to explain the profitability of momentum strategies. The evidence suggests that stocks covary 'too strongly' with each other, so that momentum profits and excess volatility in aggregate returns represent the same phenomenon.

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1. Introduction

The profitability of momentum strategies is one of the strongest and most puzzling asset-pricing anomalies. Jegadeesh and Titman (1993) show that trading strategies which buy intermediate-term winners (stocks in the top return decile over the past 3 to 12 months) and sell intermediate-term losers (stocks in the bottom decile) generate significant profits. For example, an equal-weighted momentum portfolio based on past 12-month returns earns an average profit of 6.8% in the six months after formation. Momentum is puzzling, from an efficient-markets perspective, because it suggests that risk increases following positive stock returns, contrary to the intuition that leverage and equity risk should both decline. Perhaps not surprisingly then, Jegadeesh and Titman (1993) and Fama and French (1996) find that risk-adjustment tends to accentuate, rather than explain, momentum profits. These results are often interpreted as evidence that investors underreact to new information.

This paper investigates the autocorrelation patterns in stock returns to better understand the source of momentum profits. Lo and MacKinlay (1990) show that the profitability of return-based trading strategies can be decomposed into three components: a component that relates to autocorrelation in returns, a component that relates to cross-serial correlation among stocks (correlation between an asset's return and the lagged returns on other assets), and a component that relates to cross-sectional variation in unconditional expected returns. Intuitively, a stock that has performed well relative to other stocks might continue to do so for three reasons: (1) the stock return is positively autocorrelated, so its own past return predicts high future returns; (2) the stock return is negatively correlated with the lagged returns on other stocks, so their poor performance predicts high future returns; and (3) the stock return has a high unconditional mean relative to other stocks, and both past and future returns reflect this high mean.

Using this decomposition, I find that negative cross-serial correlation among stocks is the principal source of momentum profits. There is no evidence that returns are positively autocorrelated, as suggested by models of underreaction. To be specific, the paper considers 15 industry and 15 size portfolios over the period 1941 – 1997. I test whether annual returns can predict returns up to 18 months in the future (strategies based on 6- and 9-month returns yield similar results). The industry portfolios generate significant momentum profits for 9 months after portfolio formation, and the size portfolios generate significant profits for all 18 months. Despite this momentum, a portfolio's annual return is almost always *negatively* correlated with future returns. The average correlation between an industry's annual return and its return two months later equals –0.007; the correlation declines monotonically to –0.070 by the tenth month and remains below –0.040 for the remaining months. (I refer to these correlations as 'autocorrelations' in a slight abuse of terminology.) The size portfolios exhibit a similar pattern, with the autocorrelations reaching –0.045 by the third month and declining to –0.070 by the tenth month. The cross-serial correlations for both sets of portfolios are also negative and tend to become more negative as the time lag increases. Importantly, the cross-serial correlations are more negative than the autocorrelations, and this spread creates positive momentum profits. Thus, momentum seems to be explained by lead-lag effects among stocks, not by persistence in returns.

The time-series properties of returns provide no evidence that investors underreact to news.[1] Instead, stocks appear to covary 'too strongly' with each other – that is, stock prices tend to covary more strongly than dividends. I present a simple model to illustrate how excess covariance, caused either by a time-varying risk premium or by investor overreaction, can generate momentum. In the first version of the model, investors receive new information about a given firm and mistakenly believe this information is relevant for other firms. Stock prices, therefore, move together more than they would if investors understood that news is firm-specific. The temporary price fluctuations are eventually reversed, giving rise to negative cross-serial correlation and positive momentum profits. In the second version of the model, prices covary too strongly because they move together in response to changes in the aggregate risk premium. I show that, under certain conditions, these fluctuations can generate momentum profits. Although the two models are highly stylized, they suggest that excess covariance might explain momentum better than underreaction.

The accumulated evidence on momentum clearly rejects the capital asset pricing model (CAPM), or more precisely, the mean-variance efficiency of the market proxy. The results in this paper also reject

[1] Lo and MacKinlay's (1990) analysis represents only one possible decomposition of momentum profits. Alternative decompositions are possible (e.g., Jegadeesh and Titman, 1995) which might suggest a more prominent

recent behavioral models of asset prices. DeLong, Shleifer, Summers, and Waldmann (1990) present a model in which prices are pushed away from fundamental value by noise traders. Their model suggests that price reversals should be strongest in small stocks (see Lee, Shleifer, and Thaler, 1991). I find instead that reversals appear most strongly in larger stocks, at least for the horizons studied in this paper. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) develop behavioral models motivated, in part, by apparent underreaction to news. They assume that momentum profits reflect positive autocorrelation in returns. Again, however, I find that stock returns are negatively autocorrelated over intermediate horizons, and there is no evidence that prices are slow to react to new information. Behavioral models need to explain why investors appear to overreact to news about one firm when evaluating the prospects of other firms.

It is also interesting to note that industries exhibit both short-term momentum and long-term reversals. Momentum profits turn negative in the 11th month after formation and become significantly negative by the 14th month. If we consider only these raw profits, there appears to be a substantial change in the way prices react to information over short versus long horizons. However, the components of profits suggest a more mild distinction between the two. For all months 2 – 18, both autocorrelations and cross-serial correlations are negative. Both grow more negative until the tenth month, at which point they have approximately the same magnitude. As a result, total profits are close to zero in month 10. The Lo and MacKinlay (1990) portfolio, which invests in the industries in proportion to their market-adjusted returns, has a profit of 0.18 with a t-statistic of 0.319 (the profit is 0.05% per dollar long). Cross-serial correlations contribute 7.03 of this profit, while autocorrelations contribute –6.97 (both are significantly different from zero). After month 10, the autocorrelations remain relatively flat but the cross-serial correlations begin to diminish. By the 15th month, cross-serial correlations contribute 3.98 to profits, autocorrelations contribute –5.29, and total momentum profits are significantly negative at -1.18. The difference between the short term and long term has more to do with changes in the relative magnitudes of autocorrelations and cross-serial correlations (both are always negative), rather than a fundamental change in investors' reaction to information. Recent attempts to integrate short-term momentum and

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role for underreaction. I discuss this further in Section 2.

long-term reversals have missed this important feature of returns.

This paper builds on recent work by Moskowitz and Grinblatt (1999) and Conrad and Kaul (1998). Moskowitz and Grinblatt show that much of the profitability of momentum strategies can be traced to industry factors. They argue that momentum in firm-specific returns contributes very little to trading profits. Based on their results, the empirical tests in the current paper focus on industry portfolios, and I confirm that industries display strong evidence of momentum. I also examine the autocorrelations patterns of size portfolios. Lo and MacKinlay (1990), and others, show that returns on large stocks lead the returns on small stocks over short horizons – lags of a few weeks or, at the longest, one month. I provide evidence of a lead-lag relation for much longer intervals, up to 18 months. The returns on large stocks tend to be negatively related to the future returns on all stocks. Further, size portfolios generate momentum profits about as large as those from industry portfolios, suggesting that size effects play an important role in momentum strategies.

Conrad and Kaul (1998), like the current paper, use Lo and MacKinlay's (1990) framework to decompose momentum profits. Conrad and Kaul examine individual stocks rather than portfolios, and conclude that cross-sectional variation in unconditional expected returns explains the majority of momentum profits (they do not even report autocorrelations and cross-serial correlations separately). They estimate that the cross-sectional variance of annual expected returns is 0.0155, for a standard deviation of 12.4%. This is an enormous estimate: if all firms' expected returns fall within a three-standard-deviation interval around a grand mean, their estimate implies a range of approximately 75% between the highest and lowest expected returns. In comparison, for the 15 size portfolios used in the current paper, the cross-sectional standard deviation of average returns equals 1.62% annually, with a range of 8.18%. The portion of momentum profits explained by average returns in this paper is 1/58th that in the Conrad and Kaul study. Although grouping stocks into portfolios undoubtedly reduces the true cross-sectional dispersion in expected returns, size portfolios probably give a truer picture of the role of unconditional means. The returns of individual stocks, which might be in the sample for only a short period, are simply too noisy to allow meaningful inferences.

The remainder of the paper is organized as follows. Section 2 reviews Lo and MacKinlay's (1990) decomposition of trading profits and adapts their analysis for the current paper. Section 3 presents several models of stock prices to illustrate the possible sources of momentum profits. Section 4 describes the return data and Section 5 discusses the main empirical results. Section 6 concludes.

2. A decomposition of momentum profits

Lo and MacKinlay (1990) analyze the profitability of trading strategies based on past returns. They show that profits depend on the lead-lag relations among stocks, not simply the autocorrelations of individual assets. Put differently, profits are determined by the full autocovariance matrix of returns, even though we typically focus on the diagonal elements when interpreting abnormal returns. This section reviews Lo and MacKinlay's decomposition and adapts the analysis for the current paper. At the end of the section, I briefly discuss alternative decompositions of trading profits.

2.1. Lo and MacKinlay's (1990) decomposition

The analysis initially considers a strategy based on one-period returns. Lo and MacKinlay focus on a particular hedge portfolio, but the intuition should apply to any strategy based on past returns. Consider a portfolio that requires no net investment (the portfolio's long position equals its short position) and invests in assets in proportion to their lagged market-adjusted returns. Specifically, the portfolio weight of asset *i* over month *t* equals

$$w_{i,t} = \frac{1}{N}(r_{i,t-1} - r_{m,t-1})\,, \tag{1}$$

where N is the number of assets, $r_{i,t-1}$ is the asset's return in month $t-1$, and $r_{m,t-1}$ is the return on the equal-weighted index in month $t-1$. The portfolio invests most heavily in stocks with the highest returns; any asset that performed above average is given positive weight in the portfolio and any asset that performed below average is given negative weight. Also, since $r_{m,t-1}$ is the return on the equal-weighted index, it is easy to show that the weights sum to zero.

This portfolio provides an exceptionally convenient framework for understanding the source of trading profits. Assume that returns are generated by a covariance-stationary process with unconditional mean $E[r_t] = m$, an $N\times 1$ vector, and autocovariance matrix $E[(r_t - m)(r_{t-1} - m)'] = \Omega$. The portfolio return in month t equals

$$p_t = \sum_i w_{i,t} r_{i,t} = \frac{1}{N} \sum_i (r_{i,t-1} - r_{m,t-1}) r_{i,t} \ . \tag{2}$$

Therefore, the expected profit is

$$\begin{aligned} E[p_t] &= \frac{1}{N} E\left[\sum_i r_{i,t-1} r_{i,t}\right] - \frac{1}{N} E\left[r_{m,t-1} \sum_i r_{i,t}\right] \\ &= \frac{1}{N} \sum_i (\rho_i + \mu_i^2) - \frac{1}{N^2} E\left[\sum_i r_{i,t-1} \sum_i r_{i,t}\right], \end{aligned} \tag{3}$$

where asset *i* has expected return m_i and autocovariance r_i. After a bit of manipulation,

$$E[p_t] = \frac{1}{N} \mathrm{tr}(\Omega) - \frac{1}{N^2} \iota' \Omega \iota + s_m^2 , \tag{4}$$

where ι is an $N\times 1$ vector of ones, s_m^2 is the cross-sectional variance of unconditional expected returns, and tr(·) denotes the sum of the diagonal terms. The first term is the average autocovariance of individual assets and the second term is the autocovariance of the equal-weighted index. Although we will focus on a slightly different version of eq. (4), this equation emphasizes the connection between momentum profits and the autocorrelation of aggregate returns (see also Lehmann, 1990).

We can re-arrange the expression to separate the components that depend on autocovariances and cross-serial covariances:

$$E[\pi_t] = \frac{N-1}{N^2} \mathrm{tr}(\Omega) - \frac{1}{N^2}\left[\iota' \Omega \iota - \mathrm{tr}(\Omega)\right] + s_m^2 . \tag{5}$$

In this equation, the first term depends only on the diagonal elements of Ω (the autocovariances) and the second term depends only on the off-diagonal terms (the cross-serial covariances). The third term arises because momentum strategies, by their nature, tend to invest in stocks with high unconditional expected returns: the strategy picks stocks with high past returns, and on average, stocks with high realized returns also have high unconditional means. This effect will typically be small, but will be greater when there is more dispersion in unconditional means.

Ignoring the third component, the decomposition in eq. (5) says that momentum profits can arise from two primary sources. First, stocks might be positively autocorrelated, implying that a firm with a high return today is expected to have a high return in the future. Second, stocks might be negatively cross-serially correlated, implying that a firm with a high return today predicts lower returns on other stocks in the future. In the second scenario, stocks that do well today continue to perform *relatively* well in the future only because other stocks do poorly. This phenomenon is more difficult to interpret than positive autocorrelation. Section 3 shows that negative cross-serial correlation is closely linked to 'excess' covariance among stocks. If stock prices covary more strongly than dividends, prices will contain temporary components that induce negative cross-serial correlation.

2.2. Trading strategies based on multiple-period returns

The trading strategy above is based on one-month returns. Jegadeesh and Titman (1993), however, find momentum profits for intermediate time-horizons of three to 12 months. The decomposition requires a small modification for strategies based on multiple-period returns.

To be specific, the empirical tests focus on a momentum portfolio with weights proportional to excess 12-month returns:

$$w_{i,t+k} = \frac{1}{N}(r_{i,t}^{12} - r_{m,t}^{12}), \tag{6}$$

where $w_{i,t+k}$ is the portfolio weight in month $t+k$ and $r_{i,t}^{12}$ denotes the 12-month return ending in period t. The variable k is included in the subscript because I investigate the portfolio's profitability for many months following the formation date. Notice that each month after portfolio formation is considered separately; the tests examine monthly returns (k = 1 to 18) for trading strategies based on lagged 12-month returns. To decompose the profitability of this portfolio, assume that annual returns have unconditional mean $E[r_t^{12}] = g$ and the covariance matrix between month $t+k$ returns and lagged 12-month returns equals $E[(r_{t+k} - m)(r_t^{12} - g)'] = D_k$. The expected profit in month $t+k$ is

$$E[\pi_{t+k}] = \frac{N-1}{N^2}\text{tr}(\Delta_k) - \frac{1}{N^2}\left[\iota'\Delta_k\iota - \text{tr}(\Delta_k)\right] + s_{m,g}, \tag{7}$$

where $s_{m,g}$ is the cross-sectional covariance between unconditional one-month and 12-month expected returns. Compared with the one-month strategy, this equation simply substitutes Δ_k in place of the first-order autocovariance matrix and $s_{m,g}$ in place of the cross-sectional variance of one-month expected returns. Economically, the decomposition does not change. Expected momentum profits are decomposed into three components depending on 'autocorrelations', cross-serial correlations, and unconditional expected returns. We could further relate the profitability of the 12-month strategy to the autocovariances of monthly returns, but the simple decomposition above will be adequate for our purposes.

2.3. A caveat: alternative decompositions of momentum profits

The discussion so far has closely followed Lo and MacKinlay's (1990) analysis. In the remainder of the paper, I also follow Lo and MacKinlay's lead by interpreting positive autocovariances as evidence of investor underreaction. To the extent that momentum profits are explained by negative cross-serial correlation, I interpret this as evidence against the underreaction hypothesis. I note, however, that there are alternative ways to decompose profits which might suggest a more prominent role for underreaction. For example, firm- or industry-specific components of returns might be positively autocorrelated, consistent with underreaction, while total returns are negatively autocorrelated because investors overreact to macroeconomic news. This combination of under- and overreaction seems a bit contrived, and I am not aware of any behavioral model that predicts it.

We can actually make a stronger observation: mechanically, we *must* be able to find some decomposition that implies firm-specific returns are positively autocorrelated and explain momentum profits. To see this, define the firm-specific portion of returns very simply as the difference between the firm's return and the equal-weighted index return:

$$fs_{i,t} \equiv r_{i,t} - r_{m,t}. \tag{8}$$

Using this definition, the expected profit on the momentum portfolio can be decomposed as:

$$\begin{aligned} E[p_t] &= \frac{1}{N}\sum_i E\left[fs_{i,t-1} r_{i,t} \right] \\ &= \frac{1}{N}\sum_i \mathrm{cov}(fs_{i,t-1}, fs_{i,t}) + s_m^2, \end{aligned} \tag{9}$$

where the second line uses the fact that firm-specific returns sum to zero across stocks. This equation says that momentum profits, *by construction*, equal the average autocovariance of firm-specific returns.

The problem with this decomposition is that it ignores the underlying reason that firm-specific returns are positively autocorrelated. $fs_{i,t}$ can predict returns either because the stock's own return is positively related to future returns or because the market return is negatively related to future returns. These two possibilities represent two fundamentally different phenomena, but the mechanical decomposition in eq. (9) does not distinguish between them. It seems difficult to argue that momentum is caused by underreaction if the profits are explained by a negative relation between a firm's return and past market returns. Lo and MacKinlay's (1990) decomposition captures, and in fact highlights, the difference between the two sources of profits. For this reason, I rely on their analysis to interpret the empirical results.

3. The economic sources of momentum

Section 2 considered the statistical sources of momentum. This section discusses instead the underlying economic causes. I present four simple models of stock prices that all generate momentum in returns. The models capture a wide range of price behavior: stock prices follow a random walk; investors underreact to new information; investors overreact to information about one firm when evaluating the prospects of other firms; and stock prices move in response to changes in the aggregate risk premium. The models are meant to illustrate the basic ideas, not to be accurate descriptions of stock prices.

Each of the models is based on the following representation of stock prices, adapted from Summers (1986) and Fama and French (1988). Assume that the vector of log prices, p_t, can be separated into permanent and transitory components (ignore dividends):

$$p_t = q_t + e_t, \tag{10a}$$

where q_t, an $N\times1$ vector, follows a random walk with drift and e_t is a covariance-stationary process with unconditional mean zero. We will become more precise about how q_t and e_t covary with each other below. The logic behind this equation is that prices will follow a random walk if expected returns are constant over time; time-variation in expected returns implies that prices will also contain a temporary, or mean-reverting, component. Depending on our assumptions about the time-series properties of e_t, we can represent many different types of stock behavior. The four illustrative models below consider different stochastic processes for e_t that all generate momentum in returns.

The random walk component, q_t, can be thought of as the present value of expected dividends discounted at a constant rate (the unconditional expected return). Innovations in q_t will be interpreted as news about dividends, while innovations in e_t will be interpreted as news about expected returns (see Campbell, 1991). The vector q_t follows the process

$$q_t = m + q_{t-1} + h_t, \tag{10b}$$

where m is the expected drift and h_t is white noise with mean zero and covariance matrix Σ. Combining with the equation above, continuously compounded stock returns are given by

$$\begin{aligned} r_t &= p_t - p_{t-1} \\ &= m + h_t + De_t, \end{aligned} \tag{11}$$

where $De_t = e_t - e_{t-1}$. In general, e_t will be positively autocorrelated, so that price fluctuations around the random walk are persistent but temporary. Its change, $\Delta\varepsilon_t$, will be negatively autocorrelated. Shocks to dividends and shocks to expected returns may or may not be correlated, depending on the model. The vector of unconditional expected returns is $E[r_t] = m$.

3.1. Constant expected returns

I begin with the benchmark case in which prices follow a random walk. In terms of the model above, $e_t = 0$ for every t. In this case, returns are unpredictable and have covariance matrix Σ, the dividend covariance matrix. First-order autocovariances are necessarily zero:

$$\text{cov}(r_t, r_{t-1}) = E[(r_t - m)(r_{t-1} - m)'] = 0, \tag{12}$$

and expected momentum profits based on one-period returns equal

$$E[p_t] = s_m^2, \tag{13}$$

where s_m^2 is the cross-sectional variance of expected returns. As we saw above, expected profits can be positive even without predictability. The momentum portfolio tends to invest in stocks with high expected returns and short stocks with low expected returns. Moskowitz and Grinblatt (1999), Jegadeesh and Titman (1999), and the empirical results here suggest that this component of momentum profits is small. Intuitively, realized returns provide an extremely noisy measure of unconditional means, so that the momentum strategy chooses stocks primarily on noise in this model.

3.2. Underreaction

Momentum profits are typically associated with investor underreaction. In fact, many researchers equate the two ideas, and that interpretation motivates recent behavioral models of stock returns. The model in this subsection is based on the underreaction hypothesis, with its key prediction that prices only partially reflect past information.

Recall that stock prices are represented by

$$p_t = q_t + e_t, \tag{14a}$$

$$q_t = m + q_{t-1} + h_t. \tag{14b}$$

To capture underreaction, assume that the temporary component of prices is given by

$$e_t = -r\,h_t - r^2 h_{t-1} - r^3 h_{t-2} - \ldots \tag{15}$$

where $0 < r < 1$. In words, prices deviate from a random walk because they take many periods to fully incorporate news about dividends, given by the h_t's. When information arrives, prices immediately react by $(1-r)h_t$. After k periods, prices reflect $(1-r^k)$ of the news received at t, implying that prices slowly incorporate past information. Returns in the model are given by

$$r_t = m + (1-r)h_t + (r-1)\,e_{t-1}. \tag{16}$$

Current returns partially reflect h_t and partially reflect old news.

Underreaction decreases the volatility of returns and, more importantly, induces positive autocorrelation in returns. In particular, the first-order autocovariance matrix is

$$\text{cov}(r_t, r_{t-1}) = \left(r\,\frac{1-r}{1+r} \right)\Sigma. \tag{17}$$

where Σ is the dividend covariance matrix. The expression in parentheses is positive, which implies that stocks are positively autocorrelated. Further, cross-serial correlations will tend to be positive since the autocovariance matrix is proportional to the covariance matrix of returns. Using Lo and MacKinlay's (1990) decomposition, momentum profits equal

$$E[p_t] = r\,\frac{1-r}{1+r}\left[\frac{1}{N}\,\mathrm{tr}(\Sigma) - \frac{1}{N^2}\,i'\Sigma i\right] + s_m^2. \tag{18}$$

Again, the expression in brackets must be positive because Σ is a covariance matrix. Not surprisingly, underreaction leads to momentum. Notice also that any portfolio, and in particular the equal-weighted index, will be positively autocorrelated in this model. We will see below that alternative models of momentum can produce negatively autocorrelated market returns.

3.3. Overreaction

Investor underreaction, along with positive autocorrelation, is the most common interpretation of momentum profits. We saw in Section 2, however, that lead-lag relations among stocks can also induce momentum. The final two models illustrate possible sources of negative cross-serial correlation in returns. Both models contain 'excess' covariance between stocks: prices tend to covary more strongly than dividends. The first model, in this subsection, assumes that investors overreact to news about one firm when evaluating the prospects of other firms. The second model assumes that the market risk premium changes over time.

The central feature of the model here is that investors misinterpret firm-specific news. Once again, recall that the basic model for prices is given by:

$$p_t = q_t + e_t, \tag{19a}$$

$$q_t = m + q_{t-1} + h_t. \tag{19b}$$

To highlight the central ideas, assume for simplicity that shocks to dividends are completely asset specific, or cov(h_t) = $s_h^2 I$, where I is an $N \times N$ identity matrix. However, investors mistakenly believe that news about one asset also contains relevant information about other assets, so that prices covary positively with each other. That is, although investors correctly assess how each asset's news affects its own value, they tend to 'overreact' to this information when valuing other assets. Assume that the temporary component of stock prices equals

$$e_t = Bh_t + Br\,h_{t-1} + Br^2 h_{t-2} + \dots, \tag{20}$$

where $0 < r < 1$ and B is an $N \times N$ matrix that has zero diagonal terms (investors understand how each asset's news affects in own value) and positive off-diagonals (investors overreact when valuing other assets). When new information arrives, prices immediately react by $(I+B)h_t$. After k periods, prices reflect $(I+r^{k-1}B)$ of the news received at t, so the pricing error goes to zero as k becomes large. We will put additional restrictions on the matrix B below, but the idea is that B determines how much stocks covary with each other. Pric es deviate from a random walk because investors temporarily believe that $h_{i,t}$ contains information about all stocks.

Fluctuations around a random walk are persistent but temporary. In particular,

$$e_t = r\, e_{t-1} + Bh_t, \tag{21}$$

and returns equal

$$r_t = m + (I+B)h_t + (r - 1)e_{t-1}. \tag{22}$$

Because of the overreaction, returns become more volatile and negatively autocorrelated. The variance of returns equals

$$\text{cov}(r_t) = s_h^2 \left[I + B + B' + \frac{2}{1+r} BB' \right], \tag{23}$$

which has larger diagonal terms than the covariance matrix of h_t and positive off-diagonals, representing excess covariance. The first-order autocovariance matrix is given by

$$\text{cov}(r_t, r_{t-1}) = s_h^2 (r - 1) \left[B + \frac{1}{1+r} BB' \right], \tag{24}$$

which is everywhere negative since B is assumed to have only non-negative terms and $r < 1$. In other words, both the autocorrelations and cross-serial correlations are negative, consistent with the intuition that investors overreact to news about dividends. This also implies that the equal-weighted index return is negatively autocorrelated.

Without further restrictions on the matrix B, we cannot sign momentum profits: either the negative autocovariances or the negative cross-serial covariance might dominate. Intuitively, it seems reasonable to assume that news about one firm would have a smaller, but positive, effect on other stocks. In particular, assume that the matrix B equals

$$B = b\ [ii¢ - I], \tag{25}$$

where b is a scalar such that $0 < b < 1$. The matrix B has zero diagonals and b everywhere else. The symmetry of the matrix is assumed for convenience. More importantly, the restriction on b implies that a shock to firm i has a smaller effect on other firms than on itself. With this restriction, momentum profits equal

$$E[p_t] = s_h^2 (r - 1) \frac{(N-1)}{N} b \left[\frac{b}{1+r} - 1 \right] + s_m^2, \tag{26}$$

which is positive for $0 < b < 1$. As long as the type of overreaction described in this section is not too large, then expected momentum profits will be positive.

3.4. Time-varying risk premium

Overreaction is only one possible source of excess covariance. We can also generate excess covariance without assuming any irrationality. Perhaps the easiest way would be to simply assume that firms' risks change over time as a positive function of lagged returns. That possibility seems unlikely, so I take an alternative approach. Specifically, I assume that excess covariance is caused by time-variation in the aggregate risk premium. The implications of this model for covariances and autocovariances are similar to those of the overreaction model.

Recall for the last time the basic model of stock prices:

$$p_t = q_t + e_t, \tag{27a}$$

$$q_t = m + q_{t-1} + h_t. \tag{27b}$$

If changes in the macroeconomic risk premium drive temporary price movements, then all asset prices should fluctuate together in a specific way; the covariance matrix of e_t cannot be chosen arbitrarily. Specifically, assume that price fluctuations around a random walk are perfectly correlated across assets, so that

$$e_t = x_t\, b, \tag{28}$$

where x_t is a positively autocorrelated scalar process with mean zero and b is an $N{\times}1$ vector that describes the sensitivity of asset prices to changes in the risk premium. I assume that all elements of b are positive, so that expected returns tend to move together over time. The notation b is not accidental: if each asset's risk is constant, then price fluctuations around the random walk should be related to the asset's risk. Suppose, for example, the CAPM holds and market betas are constant. Then changes in firms' expected returns are proportional to their betas, implying that temporary price fluctuations should also be closely linked to firms' betas. Although I make no assumption here about the validity of the CAPM, the notation b is chosen to capture this intuition.

In this model, stocks covary 'too strongly' because all stocks are sensitive to changes in the market risk premium. Returns are given by

$$r_t = m + h_t + bDx_t, \tag{29}$$

where $Dx_t = x_t - x_{t-1}$. It seems reasonable to assume that Dx_t is positively correlated with h_t. The vector h_t measures news about dividends, while Dx_t measures the price effect of changes in the risk premium. If positive shocks to dividends are associated with decreases in the risk premium, then Dx_t and h_t will be positively related. This assumption suggests, for example, that the market's expected return should be lower during expansions than recessions, and is consistent with empirical evidence (e.g., Fama and French, 1989; Campbell, 1991).

Assume for simplicity that x_t follows an AR(1) process:

$$x_t = r\,x_{t-1} + n_t. \tag{30}$$

The covariance between innovations of the dividend process and Dx_t equals

$$d \equiv \text{cov}(h_t, Dx_t) = \text{cov}(h_t, n_t), \tag{31}$$

where the last equality follows from the fact that h_t is uncorrelated with prior information. All elements of d are assumed to be positive, consistent with the intuition in the previous paragraph. The covariance matrix of returns equals

$$\text{cov}(r_t) = \Sigma + s^2_{\Delta x}\, bb¢ + bd¢ + db¢. \tag{32}$$

Because all elements of $\text{cov}(r_t)$ are greater than Σ, this equation implies that time-variation in the risk premium increases the variances and covariances of returns. The first-order autocovariance matrix is

$$\text{cov}(r_t, r_{t-1}) = \rho_{\Delta x}\, \beta\beta' + (\rho - 1)\, \beta\delta', \tag{33}$$

where $\rho_{\Delta x} < 0$ is the autocovariance of Δx_t. Like the prediction of the overreaction model, return autocorrelations and cross-serial correlations are both negative. It is also immediate that the return on any portfolio, and in particular the equal-weighted index, is negatively autocorrelated.

Momentum profits in the model take a particularly simple form. Using the decomposition in Section 2, the profitability of the momentum strategy is

$$E[\pi_t] = \rho_{\Delta x}\, \sigma_\beta^2 + (\rho - 1)\sigma_{\beta,\delta} + \sigma_m^2, \tag{34}$$

where σ_β^2 is the cross-sectional variance of β and $\sigma_{\beta,\delta}$ is the cross-sectional covariance between β and δ. To interpret eq. (34), recall that δ equals the covariance between dividends and temporary price movements, while β measures the sensitivity of stock prices to changes in the risk premium.

Ignoring the last term, expected profits are positive if $\sigma_{\beta,\delta}$ is negative and sufficiently large to outweigh $\rho_{\Delta x}\sigma_\beta^2$. In other words, we need stocks whose prices are sensitive to changes in the risk premium (high β_i) to have cashflows that covary relatively little with changes in the risk premium (low δ_i). This condition is plausible. For example, Fama and French (1989) find that the risk premium is higher in recessions than expansions. Further, we might expect that the fortunes of small firms are more sensitive to business conditions than those of large firms. Together, these observations suggest that the cashflows of small stocks will covary relatively strongly with the risk premium (high δ_i), because both are tied to the business cycle. On the other hand, we might expect that movements in the risk premium have a relatively small effect on the prices of small stocks (low β_i). Intuitively, the price effect of a change in the risk premium should be related to the expected duration of the firm's cashflows. If small stocks have a shorter duration than large stocks, then movements in the risk premium should effect the prices of small stocks less. The point here is not to argue that we should expect momentum in returns, but only to provide some intuition about the conditions that would lead to momentum.

3.5. Summary

Without question, underreaction would induce momentum in returns, but it is not the only possible cause. The key to distinguishing among the potential sources of momentum is the autocovariance matrix of returns. If investors underreact to new information, the elements of the autocovariance matrix should be positive, and both individual assets and portfolios will be positively autocorrelated. Overreaction or a time-varying risk premium predict instead that autocorrelations and cross-serial correlations will be negative. Further, under some additional restrictions in both models, expected momentum profits can be positive. The models provide a framework for interpreting the empirical results.

4. Data and descriptive statistics

The empirical tests examine industry and size portfolios. I use portfolios, rather than individual stocks, for several reasons. First, Moskowitz and Grinblatt (1998) argue that momentum is driven primarily by industry factors in returns. They show, for example, that momentum strategies based on industry portfolios are nearly as profitable as momentum strategies based on individual stocks. Further, momentum in individual stocks is largely attenuated when the tests control for industry returns. I examine size portfolios because prior research identifies interesting lead-lag relations between large and small stocks. Lo and MacKinlay (1990) find that returns on large stocks seem to lead returns on small stocks by one or two weeks (see also Boudoukh, Richardson, and Whitelaw, 1994; Badrinath, Kale, and Noe, 1995). In addition, analyst following, liquidity, and investor holdings (individual vs. institutional) all depend on a stock's market value, and size portfolios provide evidence on whether these differences are important for autocorrelation patterns.

I look at portfolios for more practical reasons as well. Most importantly, statistical inference is much easier for portfolios than for individual stocks. Lo and MacKinlay (1990) derive the asymptotic properties of their decomposition, but the small-sample properties are unknown. Their asymptotic results are not likely to be very accurate for individual stocks, many of which have short histories. It is also much easier to analyze small-sample biases and to simulate the sampling distribution when the number of assets remains constant over time. As a minor benefit, the portfolios permit me to report detailed results for different types of stocks, rather than simply averages across all firms.

The costs of using portfolios seem small. Like individual stocks, both sets of portfolios generate considerable momentum profits. Also, all the models above indicate that portfolios should exhibit the same patterns as individual stocks. The underreaction story suggests that individual assets and portfolios will both be positively autocorrelated, and the overreaction and time-varying risk premium stories suggest that individual assets and portfolios will both be negatively autocorrelated. It seems reasonable to assume that investor underreaction, if present, would show up in portfolio returns.

The portfolios consist of all NYSE, AMEX, and NASDAQ stocks classified as ordinary common shares on the Center for Research in Security Prices (CRSP) tapes. I calculate monthly returns from January 1941 through December 1997 (684 months) for 15 industry portfolios and 15 size portfolios. The number of portfolios was chosen to provide reasonable cross-sectional variation in portfolio characteristics, without spreading stocks too thinly across portfolios. I start the sample in 1941 so that the Depression era does not dominate the results, and because Jegadeesh and Titman (1993) find that momentum profits are negligible, or possibly negative, from 1927 through 1940. While focusing only on the post-1940 period undoubtedly induces data-snooping biases, there is no obvious reason that these biases should affect the components of momentum profits differently.

The industry portfolios are based on two-digit SIC codes as reported by CRSP. I use the historical SIC codes, not the 'header' codes, for this classification. Although SIC code definitions can change over time, I did not want to form portfolios using the header codes because of look-ahead bias. For the most part, the industries consist of consecutive two-digit codes, although some exceptions were made when deemed appropriate (details available on request). The size portfolios are formed based on the market value of equity in the previous month, with breakpoints determined by equally-spaced NYSE percentiles. Both the industry and size portfolios are updated monthly, and the tests primarily examine value-weighted returns.

Table 1 reports summary statistics for the portfolios. The average monthly returns for the industry portfolios range from 0.92% for utilities and telecommunication firms to 1.30% for the service industry (entertainment, recreation, and services), for a relatively small annualized spread of 4.6%.

Coincidentally, these industries also have the lowest (3.43%) and highest (6.05%) standard deviations, respectively. The table shows that the industries are fairly well diversified. Over the sample period, all industries other than 'petroleum' average more than 95 stocks. The size portfolios exhibit a bit more cross-sectional dispersion than the industry portfolios. Their average monthly returns range from 1.00% for the largest stocks to 1.59% for the smallest stocks, for an annualized spread of 7.1%. Again, these portfolios have the lowest (3.97%) and highest (7.17%) standard deviations as well. Because the breakpoints of the size portfolios are determined by NYSE percentiles, the small-stock portfolio has many more firms than the larger portfolios, on average more than 1,100 firms over the sample period. The small-stock portfolio represents, however, less than 1% of total market value.

5. Empirical results

This section analyzes momentum strategies based on the industry and size portfolios. I first show that both sets of portfolios generate strong momentum profits for horizons of at least 9 months, consistent with the evidence in Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999). Subsequently, I investigate the autocorrelations patterns of these portfolios and decompose momentum profits using Lo and MacKinlay's (1990) decomposition.

5.1. Methodology

Jegadeesh and Titman (1993) find momentum over intermediate horizons of three to 12 months. Their results suggest that the trading strategy based on annual returns is 'the most successful.' Moskowitz and Grinblatt (1999) confirm that the 12-month strategy generates strong profits using industry portfolios. For simplicity, then, I focus on the profitability of 12-month trading strategies; the results using six- and nine-month lagged returns are similar, although not as strong.

As discussed in Section 2, the momentum portfolio invests in assets in proportion to their market-adjusted returns:

$$w_{i,t+k} = \frac{1}{N}(r_{i,t}^{12} - r_{m,t}^{12}), \tag{35}$$

where $w_{i,t+k}$ is the portfolio weight in month $t+k$, $r_{i,t}^{12}$ is the asset's 12-month return ending in month t, and $r_{m,t}^{12}$ is the return on the equal weighted index over the same period. The empirical tests examine the portfolio's return for up to 18 months (k = 1 to 18) after the formation date.

Notice that the portfolio weights sum to zero. As a result, the weights can be scaled up or down by any amount without affecting the basic strategy. The great advantage of the specific portfolio identified by eq. (35) is that the expected profit can be readily decomposed into its three components. Unfortunately, the magnitude of the profits is difficult to interpret because the scale of the long and short positions changes every month. To ease the interpretation of the results, I also report the average return on a portfolio that invests in the same proportions, but that scales the weights so that it has \$1 long and \$1 short every period. The profits of this strategy can be interpreted as the difference in returns between a portfolio of winners and a portfolio of losers. Additionally, I also estimate cross-sectional regressions of monthly returns on lagged annual returns. Fama (1976) shows that the slope coefficient in these regressions can be interpreted as the return on a zero-investment portfolio. In fact, this portfolio is simply another re-scaling of the weights in eq. (35).

I examine the profitability of these portfolios for 18 months following the formation date. To reduce the volume of evidence reported, the tables only show results for every odd month (1, 3, 5, …, 17); the discussion in the text will sometimes refer to the missing months. For each month, the estimated profit simply equals the average return over the sample period. The standard error of the average is determined by the time-series standard deviation of the returns.

5.2. Total momentum profits

Table 2 reports momentum profits using the industry portfolios. In this table, 'LM portfolio' refers to the portfolio described by eq. (35), '\$1 long-short' re-scales this portfolio to have \$1 long and short, and 'CS regressions' is the slope coefficient from cross-sectional regressions. Consistent with Moskowitz and Grinblatt (1999), industries exhibit strong momentum. All three momentum strategies produce significant positive profits for up to nine months after formation, with many of the estimates several standard errors above zero. For the strategy based on 12-month returns, the profit on the \$1 long-short portfolio equals 0.67% (t-statistic of 6.22) in the month immediately following formation, and the profits decline steadily to 0.26% (t-statistic of 2.46) after seven months. The profits based on 6-month returns remain significant for nine months, but are somewhat less regular. They equal 0.51% (t-statistic of 4.87) in the first month, drop to 0.26% (t-statistic of 2.41) in the third month, and then grow again to 0.35% (t-statistic of 3.43) in the ninth month after formation.

The table also finds reversals at longer horizons. For the strategies based on 12-month returns, momentum profits turn negative in the 11th month after formation. They become significantly negative, equal to –0.19% per dollar long (t-statistic of –1.82), by the 14th month and remain at this level for the remaining months. The results for the 6-month strategy are similar, with the profit significantly negative after the 14th month depending on which re-scaling of the momentum portfolio you consider. In results not reported, the profits remain negative, but not significant, when I extend the tests out to 2 years after formation. The results are consistent with the firm-level evidence of Jegadeesh and Titman (1993).

Focusing on short-run momentum, the average profits on the $1 long-short portfolio are similar to the estimates reported by Moskowitz and Grinblatt (1998) for the period 1963 through 1995 (they look at the returns on the top and bottom performing industries). The returns per dollar long are somewhat smaller than returns based on individual securities, but the statistical significance is typically as large. For example, Jegadeesh and Titman (1993) report average returns for a portfolio that buys extreme winners (stocks in the top return decile over the prior 12 months) and sells extreme losers (stocks in the bottom decile). Over the three months after formation, this portfolio has an average return of 1.31% per month with a t-statistic of 3.74. The $1 long-short portfolio in Table 2 has an average return approximately 1/2 as large over three months, but the t-statistic is 5.02 (my sample is roughly twice as long). Also, as Moskowitz and Grinblatt note, equal-weighted portfolios generate larger momentum profits than value-weighted portfolios. For example, the momentum profit for equal-weighted industries (not reported) is 0.96% per dollar long in the first month after formation, compared with the 0.67% for value-weighted industries.

Table 3 replicates the analysis using size portfolios. Again, these portfolios exhibit strong momentum. Profits are significantly positive for at least a year after formation, with many of the average returns more than three standard errors above zero. Focusing on the 12-month strategy, the $1 long-short portfolio has an average return of 0.53% (t-statistic of 4.55) in the month following formation, and the profit declines slowly to 0.24% (t-statistic of 2.34) by month 18. This last statistic shows, somewhat surprisingly, that momentum persists for the entire 18 months. More generally, size momentum seems to last longer and decline more slowly than industry momentum. For example, the return on the $1 long-short portfolio declines from 0.53% in month 1 to 0.42% in month 7 for the size portfolios, but the return for the industry portfolios declines from 0.67% to 0.26%. Like the industry results, momentum profits based on 6-months returns are more erratic than those based on 12-month returns. The remainder of the paper focuses on the 12-month strategies.

Comparing Tables 2 and 3, short-run profits from industry and size portfolios are similar both in magnitude and significance level. Moskowitz and Grinblatt (1998) argue that momentum profits are driven primarily by industry factors in returns, rather than momentum in firm-specific returns. Although beyond the scope of the current paper, it would be interesting to repeat their tests controlling for both industry and size factors, and compare which of the two is more important. One interpretation of the evidence is that individual-firm returns contain a lot of 'noise' that does not help in predicting future returns. Sorting stocks into either industry or size portfolios might simply be an effective way to diversify away firm-specific returns. In other words, it is forming portfolios per se that is important rather than forming *industry* portfolios. A second explanation is that both size and industry factors in returns have strong momentum. Clearly, I do not want to push the argument too strongly: size portfolios are almost certainly not diversified with respect to industry, or vice versa, and the evidence is Tables 2 and 3 cannot say which is more important.

5.3. Autocorrelations

Tables 2 and 3 document significant momentum in returns. The most obvious conclusion is that investors underreact to new information, so that prices take many months to fully incorporate news. If this explanation is accurate, the returns on individual stocks and portfolios should be positively autocorrelated. Therefore, before turning to the formal decomposition of momentum profits, Tables 4 and

5 examine the autocorrelation patterns of returns.

The evidence above, and that in Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1998), indicates that a momentum strategy based on annual returns is profitable. Consequently, the tables report slope estimates from time-series regressions of monthly returns on lagged 12-month returns, rather than simple autocorrelations in monthly returns. For simplicity, I sometimes refer to the regression coefficients as autocorrelations. The 'month after formation' columns follow the same convention as the previous tables (although, strictly speaking, we are not forming momentum portfolios here). Also, each number in the table is estimated from a separate regression, not from a multiple regression on all lags simultaneously.

Table 4 reports autocorrelations for the industry portfolios. The standard errors of the individual coefficients, which I do not report, are clustered between 0.008 and 0.010. The results provide a stark contrast to the momentum profits in Table 2. At all lags except the first, the slope coefficients are almost always negative and often more than one standard error below zero. In other words, almost without exception, lagged 12-month returns are negatively associated with future returns over intermediate horizons, not positively related as the underreaction story predicts. Interestingly, the estimates increase in both magnitude and statistical significance as the time lag increases. The average autocorrelation is –0.002 (standard error of 0.007) for month 2 and decreases almost monotonically to –0.017 (standard error of 0.007) for month 13. By month 7, the average coefficient is approximately 1.5 standard errors below zero. It remains between 1.8 and 2.6 standard errors below zero until month 15. The individual coefficients are typically between one and two standard errors from zero, and many are significantly negative after month 7.[2]

To get a sense of the economic significance of the autocorrelations, suppose that an industry has an annual return that is 50% above the mean, or approximately 64.5% for the average portfolio. This return is large, equal to the 98th percentile of annual returns across all industries. Using the point estimates in Table 4, the predicted return in month 3 is 0.31% below its mean, and the predicted return declines

[2] Like true autocorrelations, the slope estimates in these regressions are biased downward. The bias is small, however, and cannot explain the negative coefficients. The bias is approximately –0.002 based on either

steadily until month 13 when it is 0.85% below its mean. Alternatively, suppose that the true slope coefficient is 1.65 standard errors above the point estimate, chosen as a reasonable upper bound for the autocorrelation. In this case, the annual return predicts that the return in month 3 will be 0.23% above the mean. The predicted effect declines to 0.07% by month 7 and reaches a minimum of –0.31% for month 13. It seems clear from any of these estimates that autocorrelations do not explain the strong momentum profits on industry portfolios.

The only result that provides any support for investor underreaction is month 1. Although the average coefficient is not significant, 13 out of the 15 are positive and three are more than 1.75 standard errors above zero. However, the coefficients likely reflect nonsynchronous trading and the weekly lead-lag relations among stocks documented by Lo and MacKinlay (1990). Perhaps more importantly, it does not seem plausible for underreaction to show up only for one month. A simple interpretation of the results for month 1 is that it takes investors up to 12 months to react to news. But if investors really react this slowly, then annual returns would also be positively related to returns in month 2, month 3, and so on (perhaps not as strongly as the month 1 relation, but still positive). Underreaction, as picked up by annual returns, should persist for more than one month. Thus, it seems likely that the positive autocorrelations for month 1 are driven by something other than underreaction.

Table 5 confirms these findings for size portfolios. The standard errors range from 0.006 to 0.010 (all are between 0.008 and 0.010 except for the three smallest portfolios), and I again report only the point estimates for simplicity. The table shows that annual returns on the size portfolios are almost always negatively correlated with future returns. The average coefficients are negative for months 2 through 18 and tend to become more negative as the time lag increases. The average is –0.005 in month 2, drops to –0.016 by month 10, and then climbs to –0.007 by month 18 (the standard error equals 0.008 for all three estimates). Once again, most of the estimates are between one and two standard errors below zero, but a number of the individual estimates are significantly negative for months 3 through 13.

In general, the table suggests that large stocks are more negatively autocorrelated than small stocks. The smallest portfolio (stocks with a market value less than the 6.6th percentile of NYSE stocks) is the

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Stambaugh's (1999) analytical results or on bootstrap simulations. Details available on request.

only portfolio with a positive slope coefficient at most lags. Remarkably, the point estimates for all other portfolios are negative in every month beyond month 2. In addition, the average coefficient for the five largest portfolios is always more negative than the average for the middle five portfolios, which in turn is always more negative than the average for the five smallest portfolios. (In statistical tests not reported, the average slopes for these three groups are often significantly different from each other). The slope estimates for portfolios 11 and 12 are reliably negative for months 3 through 13 (estimates around –0.019 with a standard error of 0.009), and the portfolios just above or just below them become significantly negative at longer lags. The pattern of coefficients across size portfolios is a bit surprising: there is a common perception that reversals for small stocks are more pronounced than for large stocks. For example, Fama and French (1988) find that 3- to 5-year autocorrelations for small stocks are typically more negative than autocorrelations for larger stocks.

The time-varying risk premium model in Section 3.4 is broadly consistent with the autocorrelation patterns in Table 5. The model assumes that the market risk premium changes over time, and that the returns on some stocks pick up movements in the risk premium better than other stocks. Empirically, Fama and French (1989) have shown that the risk premium seems to be high in recessions and low in expansions. To the extent that the returns of large firms are more closely tied to overall business conditions than the returns of small firms, for example because large firms tend to be more diversified while small firms are subject to more idiosyncratic risk, we might expect their returns to better capture information about the market risk premium. If so, large firms will tend to be more negatively related to future returns than small stocks. The pattern of slope coefficients in Table 5 might reflect this phenomenon.[3]

Of course, the autocorrelation patterns could also be generated by irrational investors, but existing behavioral models have a difficult time explaining the evidence. DeLong, Shleifer, Summers, and Waldmann (1990) develop a model of noise trading in which the beliefs of 'unsophisticated' investors fluctuate randomly over time, driving asset prices away from fundamental values. Lee, Shleifer, and

[3] The cross-serial correlations are also consistent with this explanation. Large stocks tend to be negatively related to the future returns on all portfolios. See Section 5.4.

Thaler (1991), and many others, interpret noise traders as individual investors, and argue that these traders should affect the price of small stocks more than the price of large stocks. This story implies that small stocks should display stronger evidence of mean reversion than large stocks, contrary to the evidence in Table 5. More recent behavior models also do not appear to explain the autocorrelation pattern across size deciles. Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (1998) suggest that the most successful traders will also be the most overconfident traders, leading to underreaction in returns. Presumably, large institutional traders have been the most successful traders (that is, successful traders become institutional traders). Since institutions tend to invest in larger stocks, the overconfidence story suggests that underreaction should show up most strongly in larger portfolios. Table 5 shows exactly the opposite. (Fama, 1998, makes a similar point, which motivated the discussion here).

5.4. Components of momentum profits

Overall, Tables 4 and 5 suggest that past returns are negatively associated with future returns. There is no evidence that investors underreact to information. Based on the decomposition of Lo and MacKinlay (1990), we know immediately that either cross-serial covariances or the cross-sectional dispersion in expected returns must be an important the source of momentum profits. This section formally decomposes momentum profits using their framework.

The momentum portfolio invests in assets in proportion to their market-adjusted returns over the past year. Section 2 showed that the expected return on the 'LM portfolio' is

$$E[\pi_{t+k}] = \frac{N-1}{N^2}\,\mathrm{tr}(\Delta_k) - \frac{1}{N^2}\left[\iota'\Delta_k\iota - \mathrm{tr}(\Delta_k)\right] + s_{m,g}, \tag{36}$$

where $s_{m,g}$ is the cross-sectional covariance between expected monthly and expected annual returns and $\Delta_k = E[(r_{t+k} - m)(r_t^{12} - g)']$ is the covariance matrix between month $t+k$ returns and annual returns ending in month t. As before, I will frequently refer to Δ_k as an autocovariance matrix. This equation is basically the same as Lo and MacKinlay's decomposition, except that the trading strategy analyzed here is based on multiple-period returns. The first term depends only on autocovariances, the second term depends only on cross-serial covariances, and the third term depends only on unconditional expected returns.

Unfortunately, the autocovariance matrices are too large to report for each lag. To provide a sense of the magnitude of cross-serial covariances, Table 6 reports descriptive statistics summarizing the autocorrelation matrices. The table shows the average diagonal and average off-diagonal terms for both sets of portfolios. The average autocorrelations duplicate the information in Tables 4 and 5: the autocorrelations for month 1 are positive, but quickly become negative and grow larger in absolute terms until month 13. The table shows that the cross-serial correlations exhibit a similar pattern. For the industry portfolios, the average cross-serial correlation declines from –0.002 in month 1 to –0.073 in month 10, and then slowly grows to –0.032 by month 18. The cross-serial correlations for the size portfolios are nearly the same, reaching a minimum of –0.079 in month 10. Importantly, the table shows that cross-serial correlations tend to be more negative than autocorrelations. On average, the cross-serial correlations are 0.004 less than the autocorrelations for industry portfolios and 0.008 less than the autocorrelations for size portfolios. We will see in a moment that this pattern drives the profitability of momentum strategies: autocovariances contribute negative profits to the strategy, but these are more than offset by the profits generated by negative cross-serial covariances.

The earlier autocorrelation results showed that large-stock returns are negatively related to their own future returns. That evidence raises the possibility that large stocks might also pick up information about the future returns on other stocks. To provide direct evidence on lead-lag effects, Table 7 reports the average autocorrelation matrix for the size portfolios, averaged across all lags 1 – 18. In other words, I estimate the autocorrelation matrix, Δ_k, separately for each lag and then average the matrices. Each row of the table reports the average correlation between a given portfolio's monthly return and the lagged annual returns on other portfolios. The table shows that the returns on large stocks are, in fact, negatively related to the future returns on all stocks. In the last column, for example, the 12-month return on the largest portfolio is negatively related to its own future returns, with an average correlation of –0.04. It is even more strongly related to the returns on other stocks, reaching a maximum correlation of –0.12 with the return on the smallest portfolio. On the other hand, the smallest portfolio's annual return has much less predictive power, with correlations ranging from 0.02 to –0.04 in the first column. The difference between the largest and smallest portfolios is representative of the overall matrix. In general, the correlations become more negative moving from left to right, implying that the returns on larger stocks have more predictive power than the returns on smaller portfolios.

Table 8 reports the formal decomposition of momentum profits. The column 'Auto' estimates the contribution of autocovariances, 'Cross' estimates the contribution of cross-serial covariances, and 'Means' estimates the contribution of cross-sectional dispersion in unconditional expected returns. Total profits are the sum of the three components, and simply equal the average returns reported in Tables 2 and 3 for the 'LM portfolio.'

The standard errors require some explanation. For simplicity, the table reports the same standard error for all lags. This is appropriate as long as returns are stationary. Specifically, the standard errors should be the same for all lags except that the sample sizes differ slightly, ranging from 668 to 684 months, which is too small a difference to matter (the actual estimates for different lags are similar and show no apparent pattern across lags). The more important issue concerns how the standard errors are estimated. The table shows two sets of estimates. The first set, 'LM std error,' is based on the asymptotic results of Lo and MacKinlay (1990, Appendix 2). The estimates are essentially Newey-West (1987) standard errors. The second set is based on bootstrap simulations. I generate artificial time series of returns by sampling randomly from historical returns, thereby imposing the constraint that returns are independent over time. The returns for different portfolios are sampled simultaneously to maintain the cross-sectional correlation among returns. This procedure is repeated 2000 times to generate an empirical distribution of the test statistics under the null hypothesis that all autocorrelations and cross-serial correlations are zero.

The discussion below is based on the bootstrap standard errors. The bootstrap standard errors should be a reliable guide to the small-sample distribution under the null hypothesis of no intertemporal dependence in returns. Surprisingly, the table shows that the bootstrap standard errors are roughly 35% smaller than the asymptotic standard errors. I do not have a good explanation for the difference. One possible difference is that the LM standard errors are consistent estimates even when autocorrelations and cross-serial correlations are non-zero. In contrast, the bootstrap standard errors should be accurate only under the null. As a robustness check, I have repeated the simulations allowing the equal-weighted index to follow a GARCH(1,1) process. I also assume that the volatilities of all stocks move together. The standard errors from these simulations are quite similar to those from the simple IID simulations, with less than a 5% change in the estimates.[4]

The results in Table 8 are striking: momentum profits appear to be explained entirely by negative cross-serial correlation in returns. Confirming our earlier evidence, autocorrelations almost always contribute negatively to momentum profits. The autocovariance component is negative at all lags other than month 1 and becomes more negative as the lag increases. For the industry portfolios, the estimate is –2.81 (t-statistic of –1.05) in month 3 and declines to –7.32 (t-statistic of –2.74) by month 13. Similarly, for the size portfolios, 'Auto' is –4.12 (t-statistic of –1.14) in month 3 and reaches a minimum of –6.83 (t-statistic of –1.89) in month 10. Most of the estimates are between one and two standard errors below zero, and the estimates for industry portfolios are typically more significant than those for size portfolios. For the industries, the estimates for months 8 through 16 are greater than 1.8 standard errors below zero. For the size portfolios, only months 10 and 13 are more than 1.7 standard errors from zero. Overall, the evidence is similar to the autocorrelation results in Tables 4 and 5: the autocovariances are either insignificant or marginally negative for all months 2 – 18.

In contrast, cross-serial covariances almost always contribute positively to momentum profits. Table 8 shows that 'Cross' is positive in all months other than the first. For the industry portfolios, the estimates are greater than 1.60 standard errors above zero for months 3 – 14 and many of the t-statistics are greater than two. The estimate equals 4.63 (t-statistic of 1.80) for month 3 and achieves a maximum of 7.03 (t-statistic of 2.72) in month 10. The results for the size portfolios are similar, but the statistical significance is less. The estimate grows from 5.59 (t-statistic of 1.59) in month 3 to 8.11 (t-statistic of 2.31) in month 10. The estimates between month 3 and month 14 are all more than 1.4 standard errors above zero, and the estimates from month 8 – 14 are significant at conventional levels. In short, Table 8 suggests that cross-serial correlation in returns plays an important role in momentum trading strategies. There is no evidence, either in Table 8 or in the previous tables, that prices underreact to new information.

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[4] Details available on request. I thank Ken French for suggesting the GARCH simulations.

Autocorrelations and cross-serial correlations both appear to be negative, which is most consistent with the overreaction or time-varying risk premium models of Section 3.[5]

Cross-sectional variation in unconditional expected returns has only a small effect on profits. For the industry portfolios, unconditional expected returns contribute between 0.12 and 0.14 to momentum profits. To put these in perspective, total profits range from 2.97 in month 1 to –0.89 in month 18, which are both many times larger that the profit contributed by unconditional means. For the size portfolios, expected returns contribute anywhere from 0.31 to 0.36 of momentum profits, while total profits range from 2.60 in month 1 to 1.10 in month 17. Thus, the table suggests that unconditional expected returns are not an important component of trading profits.

This finding contradicts the results of Conrad and Kaul (1998). They argue that cross-sectional variation in expected returns is the most important source of momentum. For example, Conrad and Kaul estimate that a momentum strategy based on annual returns yields a total profit of 0.701 when held for 12 months (their sample is 1962 – 1989). Cross-sectional variation in expected returns explains 1.550, or 221% (1.550 / 0.701), of the profits. Their estimates for different horizons show that unconditional means are always important.

Conrad and Kaul's conclusions are based on individual stock returns, and it seems likely that noise in the estimates of expected returns plays a important role in their analysis. The cross-sectional standard deviation of average returns implied by their estimates is 12.4%. As mentioned in the introduction, this is an enormous value, suggesting that the range between the highest and lowest average returns is roughly 75% (12.4×6). It is difficult to believe that cross-sectional variation in expected returns can be this high. In comparison, sorting stocks into deciles based on size yields an range of 8.2%, based on lagged book-to-market yields a range of 9.6%, and based on lagged returns yields a range of 15.7% (for the last two, see Fama and French, 1996). Using the maximum of these three estimates, the component of momentum profits explained by expected returns would be approximately 20 times smaller than the value reported by

[5] The decomposition suffers from a small-sample bias because autocorrelations and cross-serial correlations are both biased downward in finite samples. Simulations indicate that the bias is small and does not affect the inferences from Table 8. The bias in the autocovariance component is approximately –0.48 for industry portfolios and –0.53 for size portfolios, and the biases in the cross-serial covariance components are 0.35 and 0.47, respectively.

Conrad and Kaul [$(75.0/15.7)^2$]. These numbers suggest that the average returns on individual stocks are not a reliable guide to cross-sectional variation in expected returns. Jegadeesh and Titman (1999) discuss the methodology used by Conrad and Kaul in greater detail.

Table 8 highlights another interesting pattern. The momentum profits from industry portfolios actually turn negative in month 11 and are significantly negative in months 13 – 18. Thus, if we focus only on the total profits, there appears to be substantial discontinuity between short-term momentum and longer-term reversals, as documented previously by Jegadeesh and Titman (1993). These two phenomenon have led to several recent papers that attempt to unify underreaction and overreaction in a single framework (e.g., Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1988; Hong and Stein, 1998). However, the components of profits suggest a more mild distinction between the short term and long term. Table 8 shows that autocorrelations and cross-serial correlations are negative for all lags (other than the first), consistent with either the time-varying risk premium or overreaction stories. The primary difference between the short and long term seems to be the relative magnitudes of autocorrelations and cross-serial correlations. There is little evidence of a fundamental change in the way investors react to information. Although there is clearly a significant difference between month 3 and month 15, as reflected in total profits, it does not appear that the behavioral models can explain this difference.

6. Summary and conclusions

Jegadeesh and Titman (1993) find that stock returns exhibit significant momentum over intermediate horizons: trading strategies that buy winners and sell losers appear to earn significant risk-adjusted profits. Their results are often interpreted as evidence that returns are positively autocorrelated, and consequently, that investors react slowly to new information. However, little research has directly tested whether autocorrelations can actually explain momentum.

The empirical results in this paper show that autocorrelations do not explain momentum. Annual returns on 15 industry and 15 size portfolios are almost always negatively associated with future returns over the period 1941 – 1997. Despite this negative autocorrelation, both sets of portfolios generate significant momentum profits, comparable to the profitability of momentum strategies based on individual stocks. The apparent contradiction between negative autocorrelation and positive momentum can be explained by the lead–lag effects among stocks. Using Lo and MacKinlay's (1990) decomposition, I find that cross-serial correlation among stocks is significantly negative and large enough to produce the momentum observed for industry and size portfolios. There is no evidence that investors underreact to information.

The accumulated evidence on momentum is difficult to reconcile with traditional asset-pricing models. The empirical results here also reject the behavioral models of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). These papers are motivated by apparent underreaction to news and predict that returns will be positively autocorrelated over short horizons, contrary to the findings in this paper. They make few, if any, predictions about the cross-serial covariances that appear to cause momentum. Asset-pricing theory, grounded in either market efficiency or bahavioral finance, needs to explain why some stocks are negatively correlated with the future returns on other stocks. Section 3 showed that excess covariance in returns – stock prices covary more strongly than dividends – can lead to negative cross-serial correlation. I have not attempted to distinguish between the overreaction and time-varying risk premium models, nor do I suggest that they are the only, or even the most likely, explanations. The models are simply meant to show the link between excess co-movement and negative serial correlation.

In addition to the main results on momentum, the paper documents several interesting patterns across time horizons and across size portfolios. I find that autocorrelations and cross-serial correlations tend to become more negative as the time horizon increases. For example, the average correlation between an industry's annual return and its return two months later is -0.007, and the correlation declines to -0.070 by the 10th month. The autocorrelations seem to reach a minimum after 10 to 12 months. Cross-serial correlations exhibit the same pattern, reaching a minimum of –0.073 in month 10. I also find that the large stocks have more predictive power than small stocks. The annual return on the largest portfolios appear to be negatively correlated with their own future returns and even more strongly correlated with the future returns on small stocks. For example, the autocorrelation of the largest portfolio (the correlation between its annual return and return over the next 18 months) is –0.04, but its cross-serial correlation with the smallest portfolio is –0.12. The patterns across time and across size portfolios provide a challenge for asset-pricing theory, as well as a rich area for further empirical research.

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Table 1
Summary statistics for industry and size portfolios, 1/41 - 12/97

Each month from January 1941 through December 1997, value-weighted industry and size portfolios are formed from all NYSE, Amex, and NASDAQ stocks on CRSP. The 15 industry portfolios are formed based on two-digit SIC codes, and typically consist of firms in consecutive SIC codes (although some exceptions were made). The 15 size portfolios are formed based on the market value of equity in the previous month, with breakpoints determined by equally-spaced NYSE percentiles. The table reports the average return and standard deviation of each portfolio (in percent), the number of firms in the portfolio on average and at the end of the sample, and the percent of total market value in the portfolio on average and at the end of the sample.

	Return (%)		Number of firms		Market value (%)	
Portfolio	Mean	Std. dev.	Mean	12/97	Mean	12/97
Panel A: Industry portfolios						
Nat. resources	1.01	5.23	187	344	3.5	3.0
Construction	1.00	5.10	280	406	8.0	3.3
Food, tobacco	1.16	4.10	118	141	6.3	6.4
Consumer products	1.05	5.37	159	245	1.4	0.9
Logging, paper	1.21	5.23	112	187	3.4	3.1
Chemicals	1.08	4.56	159	440	10.9	10.5
Petroleum	1.23	4.95	36	28	11.1	3.5
Machinery	1.08	5.22	205	440	6.3	5.1
Electrical equip.	1.11	5.28	343	983	8.1	11.2
Transport equip.	1.12	5.24	95	128	6.6	3.3
Shipping	1.03	5.62	98	159	3.1	1.6
Utilities, telecom.	0.92	3.43	192	419	14.3	9.2
Trade	1.08	4.94	318	828	6.3	7.0
Financial	1.17	4.73	548	1,785	7.7	21.8
Services and other	1.30	6.05	415	1,392	2.9	10.2
Panel B: Size portfolios						
Smallest	1.59	7.17	1,188	3,057	0.9	0.9
2	1.36	6.26	286	888	0.7	0.8
3	1.32	5.91	212	650	0.8	0.9
4	1.27	5.69	176	499	0.9	1.0
5	1.26	5.55	157	414	1.1	1.2
6	1.29	5.38	145	381	1.4	1.4
7	1.24	5.25	133	313	1.7	1.6
8	1.29	5.13	120	303	2.0	2.0
9	1.17	4.96	110	252	2.5	2.2
10	1.21	4.84	105	225	3.2	2.6
11	1.18	4.87	100	228	4.1	3.9
12	1.20	4.63	96	199	5.7	4.9
13	1.11	4.44	92	183	8.3	7.3
14	1.05	4.26	89	176	13.5	13.0
Largest	1.00	3.97	88	166	53.3	56.3

Table 2
Momentum profits from industry portfolios, 1/41 - 12/97

The table reports average returns, standard errors, and t-statistics for momentum strategies based on value-weighted industry returns. The momentum portfolios are based on 6-month returns in Panel A and 12-month returns in Panel B. The 'LM portfolio' invests $w_{it} = (1/N)\ (r_{i,t-1} - r_{m,t-1})$ in asset i, where $r_{i,t-1}$ is the asset's lagged return and $r_{m,t-1}$ is the lagged return on the equal-weighted index. The '$1 long-short' portfolio invests in the same proportions, but scales the weights so that the portfolio has $1 long and $1 short. 'CS regressions' is the slope coefficent from monthly cross-sectional regressions, which also is the return on a zero-investment portfolio (Fama, 1976). Returns are reported in percent.

	Month after formation								
Strategy	1	3	5	7	9	11	13	15	17
Panel A: Based on 6-month returns									
$1 long-short	**0.509**	**0.263**	**0.382**	**0.501**	**0.351**	0.085	-0.078	-0.140	**-0.223**
std error	0.104	0.109	0.109	0.102	0.102	0.103	0.103	0.100	0.098
t-statistic	4.87	2.41	3.52	4.89	3.43	0.82	-0.76	-1.40	-2.28
LM portfolio	**1.315**	**0.694**	**0.982**	**1.507**	**1.173**	0.192	-0.475	**-0.653**	-0.473
std error	0.359	0.359	0.348	0.333	0.354	0.339	0.331	0.317	0.306
t-statistic	3.66	1.93	2.82	4.52	3.32	0.57	-1.43	-2.06	-1.55
CS regressions	**0.032**	**0.018**	**0.023**	**0.030**	**0.017**	0.006	-0.001	-0.005	**-0.017**
std error	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
t-statistic	5.61	2.88	3.67	5.10	2.94	0.97	-0.10	-0.87	-2.80
Panel B: Based on 12-month returns									
$1 long-short	**0.673**	**0.432**	**0.309**	**0.257**	0.124	-0.050	-0.128	**-0.212**	**-0.174**
std error	0.108	0.110	0.109	0.105	0.107	0.104	0.104	0.101	0.099
t-statistic	6.22	3.94	2.84	2.46	1.16	-0.49	-1.24	-2.10	-1.76
LM portfolio	**2.970**	**1.959**	**1.226**	**1.089**	0.623	-0.317	-0.826	**-1.184**	-0.844
std error	0.608	0.584	0.558	0.549	0.579	0.534	0.532	0.520	0.519
t-statistic	4.88	3.36	2.20	1.98	1.08	-0.59	-1.55	-2.28	-1.63
CS regressions	**0.026**	**0.017**	**0.013**	**0.010**	0.004	-0.001	-0.002	**-0.007**	**-0.006**
std error	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
t-statistic	6.63	4.12	3.17	2.73	1.11	-0.24	-0.60	-1.83	-1.70

Bold implies the average return is greater than 1.645 standard errors from zero.

Table 3
Momentum profits from size portfolios, 1/41 - 12/97

The table reports average returns, standard errors, and t-statistics for momentum strategies based on value-weighted size portfolios. The momentum portfolios are based on 6-month returns in Panel A and 12-month returns in Panel B. The 'LM portfolio' invests $w_{it} = (1/N) (r_{i,t-1} - r_{m,t-1})$ in asset i, where $r_{i,t-1}$ is the asset's lagged return and $r_{m,t-1}$ is the lagged return on the equal-weighted index. The '$1 long-short' portfolio invests in the same proportions, but scales the weights so that the portfolio has $1 long and $1 short. 'CS regressions' is the slope coefficent from monthly cross-sectional regressions, which also is the return on a zero-investment portfolio (Fama, 1976). Returns are reported in percent.

	Month after formation								
Strategy	1	3	5	7	9	11	13	15	17
Panel A: Based on 6-month returns									
$1 long-short	**0.268**	0.173	**0.283**	**0.523**	**0.402**	**0.261**	0.039	0.044	0.055
std error	0.122	0.118	0.119	0.125	0.116	0.100	0.104	0.098	0.109
t-statistic	2.19	1.47	2.38	4.17	3.46	2.61	0.37	0.45	0.50
LM portfolio	**1.052**	**0.787**	0.525	**1.395**	**1.016**	**1.052**	0.413	0.403	0.392
std error	0.414	0.355	0.339	0.410	0.314	0.308	0.373	0.309	0.293
t-statistic	2.54	2.21	1.55	3.40	3.23	3.42	1.11	1.31	1.33
CS regressions	**0.017**	0.001	0.014	**0.040**	**0.028**	0.015	0.002	-0.006	0.002
std error	0.010	0.011	0.010	0.010	0.011	0.010	0.010	0.011	0.010
t-statistic	1.67	0.07	1.41	3.97	2.66	1.47	0.18	-0.55	0.21
Panel B: Based on 12-month returns									
$1 long-short	**0.525**	**0.417**	**0.429**	**0.416**	**0.299**	**0.218**	**0.232**	**0.287**	**0.243**
std error	0.115	0.125	0.118	0.110	0.114	0.119	0.105	0.101	0.104
t-statistic	4.55	3.34	3.63	3.78	2.61	1.83	2.22	2.84	2.34
LM portfolio	**2.602**	**1.809**	**1.770**	**1.817**	**1.587**	**1.555**	**1.343**	**1.217**	**1.095**
std error	0.759	0.638	0.582	0.563	0.566	0.609	0.662	0.539	0.493
t-statistic	3.43	2.83	3.04	3.23	2.80	2.55	2.03	2.26	2.22
CS regressions	**0.026**	**0.018**	**0.022**	**0.025**	0.012	0.005	**0.015**	**0.019**	**0.016**
std error	0.006	0.008	0.007	0.007	0.008	0.007	0.007	0.007	0.007
t-statistic	4.03	2.26	3.10	3.43	1.52	0.72	2.08	2.48	2.35

Bold implies the average return is greater than 1.645 standard errors from zero.

Table 4
Autoregressive coefficients for industry portfolios, 1/41 - 12/97

The table reports the OLS slope coefficient when an industry portfolio's monthly return is regressed on its lagged 12-month return. In column '1', the dependent variable is the return in the first month following the 12-month return; in column '3', the dependent variable is the return in the third month following the 12-month return; etc. Table 1 describes the value-weighted industry portfolios in greater detail. The average standard error of the coefficients is 0.009.

	Month after formation								
Portfolio	1	3	5	7	9	11	13	15	17
Nat. resources	0.000	-0.011	-0.009	-0.004	-0.005	**-0.016**	**-0.019**	**-0.020**	**-0.017**
Construction	-0.001	-0.010	-0.005	-0.009	-0.015	**-0.021**	**-0.018**	-0.010	-0.009
Food, tobacco	**0.015**	0.007	0.003	0.003	-0.002	-0.004	-0.012	-0.012	-0.007
Consumer products	**0.016**	-0.004	-0.007	-0.012	**-0.018**	**-0.024**	**-0.027**	**-0.020**	**-0.018**
Logging, paper	0.004	-0.006	-0.003	-0.007	-0.010	-0.010	-0.011	-0.008	-0.009
Chemicals	0.006	0.000	0.002	-0.004	-0.011	-0.010	-0.015	**-0.016**	**-0.017**
Petroleum	-0.001	-0.006	-0.012	-0.011	-0.014	**-0.016**	**-0.017**	**-0.020**	-0.015
Machinery	0.000	**-0.019**	-0.013	-0.012	**-0.016**	**-0.018**	-0.013	0.000	-0.001
Electrical equip.	0.001	-0.009	-0.008	-0.007	-0.007	-0.010	-0.013	-0.009	-0.008
Transport equip.	0.010	-0.002	-0.005	-0.005	-0.009	**-0.018**	**-0.017**	-0.011	-0.010
Shipping	0.000	-0.013	-0.015	**-0.019**	**-0.025**	**-0.028**	**-0.024**	-0.014	-0.007
Utilities, telecom.	**0.016**	0.005	-0.004	**-0.014**	-0.014	**-0.015**	-0.014	-0.006	0.001
Trade	0.008	-0.010	-0.013	**-0.016**	-0.011	**-0.017**	**-0.025**	**-0.019**	**-0.015**
Financial	0.004	-0.011	-0.009	**-0.015**	-0.014	**-0.015**	**-0.017**	-0.011	-0.012
Services and other	0.012	-0.004	-0.008	-0.009	-0.006	-0.009	**-0.013**	-0.009	-0.006
Average	0.006	-0.006	-0.007	-0.009	**-0.012**	**-0.015**	**-0.017**	**-0.012**	-0.010
(std error)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Chi-squared	16.90	17.46	12.04	18.74	19.22	20.41	17.87	17.66	15.65
(p-value)	(0.325)	(0.292)	(0.676)	(0.226)	(0.204)	(0.157)	(0.270)	(0.281)	(0.406)

Bold implies the estimate is more than 1.645 standard errors from zero.

Table 5
Autoregressive coefficients for size portfolios, 1/41 - 12/97

The table reports the OLS slope coefficient when a size portfolio's monthly return is regressed on its lagged 12-month return. In column 1, the dependent variable is the return in the first month following the 12-month return; in column 3, the dependent variable is the return in the third month following the 12-month return; etc. Table 1 describes the value-weighted size portfolios in greater detail. The average standard error of the coefficients is 0.009.

	Month after formation								
Portfolio	1	3	5	7	9	11	13	15	17
Smallest	**0.020**	0.005	0.003	0.003	0.000	0.001	-0.001	0.001	0.000
2	**0.014**	-0.004	-0.004	-0.002	-0.003	-0.004	-0.006	-0.004	-0.006
3	0.012	-0.007	-0.006	-0.006	-0.009	-0.010	**-0.014**	-0.008	-0.006
4	0.011	-0.009	-0.007	-0.006	-0.008	-0.010	-0.012	-0.006	-0.007
5	0.008	-0.010	-0.007	-0.007	-0.009	-0.011	-0.013	-0.007	-0.007
6	0.008	-0.011	-0.008	-0.008	-0.012	-0.012	**-0.014**	-0.007	-0.008
7	0.003	-0.014	-0.012	-0.010	-0.012	**-0.015**	**-0.015**	-0.007	-0.008
8	0.004	**-0.015**	-0.012	-0.012	-0.012	-0.014	**-0.015**	-0.006	-0.007
9	0.005	-0.011	-0.009	-0.012	-0.014	**-0.017**	**-0.016**	-0.009	-0.008
10	0.003	-0.014	-0.013	**-0.017**	**-0.019**	**-0.021**	**-0.020**	-0.012	-0.012
11	-0.001	**-0.018**	**-0.016**	**-0.017**	**-0.019**	**-0.021**	**-0.019**	-0.013	-0.011
12	-0.006	**-0.021**	**-0.018**	**-0.020**	**-0.018**	**-0.018**	**-0.016**	-0.010	-0.008
13	0.000	-0.013	-0.011	-0.015	-0.015	**-0.018**	**-0.017**	-0.009	-0.010
14	-0.003	-0.015	-0.012	-0.016	**-0.017**	**-0.020**	**-0.017**	-0.008	-0.008
Largest	0.006	-0.001	-0.005	-0.010	-0.015	-0.016	**-0.019**	**-0.016**	-0.012
Average	0.006	-0.011	-0.009	-0.010	-0.012	**-0.014**	**-0.014**	-0.008	-0.008
(std error)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Chi-squared	31.94	28.75	16.95	16.75	14.61	17.31	17.32	18.48	10.83
(p-value)	(0.007)	(0.017)	(0.322)	(0.334)	(0.480)	(0.300)	(0.300)	(0.238)	(0.764)

Bold implies the estimate is more than 1.645 standard errors from zero.

Table 6
Average autocorrelations and cross-serial correlations, 1/41 - 12/97

The table reports average statistics for (1) the correlation between a portfolio's monthly return and its own lagged 12 month return ('average autocorrelation'), and (2) the correlation between a portfolio's monthly return and the lagged 12-month returns on other portfolios ('average cross-serial correlation'). Table 1 describes the value-weighted industry and size portoflios in greater detail.

	Month after formation								
Correlation	1	3	5	7	9	11	13	15	17
Panel A: Industry portfolios									
Average auto-correlation	0.027	-0.025	-0.030	-0.040	-0.050	-0.065	-0.073	-0.053	-0.043
Average cross-serial correlation	-0.002	-0.046	-0.044	-0.052	-0.057	-0.063	-0.065	-0.041	-0.034
Panel B: Size portfolios									
Average auto-correlation	0.028	-0.045	-0.038	-0.044	-0.052	-0.059	-0.062	-0.035	-0.034
Average cross-serial correlation	0.020	-0.054	-0.049	-0.053	-0.060	-0.067	-0.070	-0.042	-0.040

Table 7
Average autocorrelation matrix for size portfolios, 1/41 - 12/97

Each row of the table reports the average correlation between a given size portfolio's monthly return and the lagged 12-month returns of all portfolios. The correlations are estimated for each lag separately, months 1 through 18, and the average correlation across all lags is reported. The diagonal elements of the matrix are reported in bold to facilitate reading the table, not to indicate statistical significance. Table 1 describes the value-weighted size portfolios in greater detail.

	Lagged 12-month returns														
Portfolio	Small	2	3	4	5	6	7	8	9	10	11	12	13	14	Large
Small	**0.02**	-0.01	-0.02	-0.03	-0.04	-0.04	-0.05	-0.06	-0.05	-0.07	-0.08	-0.06	-0.08	-0.09	-0.12
2	0.01	**-0.01**	-0.02	-0.03	-0.04	-0.04	-0.05	-0.06	-0.04	-0.06	-0.07	-0.05	-0.06	-0.08	-0.10
3	-0.01	-0.02	**-0.03**	-0.04	-0.04	-0.04	-0.05	-0.06	-0.05	-0.06	-0.08	-0.06	-0.07	-0.08	-0.10
4	0.01	-0.01	-0.02	**-0.03**	-0.03	-0.03	-0.04	-0.05	-0.04	-0.05	-0.07	-0.04	-0.05	-0.06	-0.08
5	-0.01	-0.02	-0.03	-0.04	**-0.04**	-0.04	-0.05	-0.05	-0.04	-0.05	-0.07	-0.05	-0.06	-0.07	-0.08
6	-0.01	-0.03	-0.03	-0.04	-0.04	**-0.04**	-0.05	-0.05	-0.04	-0.05	-0.07	-0.05	-0.05	-0.06	-0.08
7	-0.01	-0.02	-0.03	-0.04	-0.04	-0.04	**-0.05**	-0.05	-0.04	-0.05	-0.06	-0.05	-0.05	-0.06	-0.07
8	-0.01	-0.02	-0.02	-0.03	-0.03	-0.03	-0.04	**-0.04**	-0.03	-0.05	-0.06	-0.04	-0.05	-0.06	-0.07
9	-0.01	-0.03	-0.04	-0.05	-0.05	-0.05	-0.05	-0.06	**-0.05**	-0.06	-0.07	-0.06	-0.06	-0.07	-0.08
10	-0.03	-0.04	-0.04	-0.05	-0.05	-0.05	-0.06	-0.06	-0.05	**-0.06**	-0.07	-0.05	-0.06	-0.07	-0.08
11	-0.03	-0.04	-0.04	-0.05	-0.04	-0.04	-0.05	-0.06	-0.04	-0.06	**-0.07**	-0.05	-0.05	-0.06	-0.07
12	-0.03	-0.04	-0.05	-0.06	-0.05	-0.05	-0.06	-0.07	-0.05	-0.07	-0.08	**-0.06**	-0.06	-0.07	-0.07
13	-0.03	-0.04	-0.04	-0.05	-0.04	-0.04	-0.05	-0.06	-0.04	-0.06	-0.07	-0.05	**-0.05**	-0.06	-0.06
14	-0.03	-0.04	-0.05	-0.06	-0.05	-0.05	-0.05	-0.06	-0.04	-0.06	-0.06	-0.05	-0.05	**-0.05**	-0.06
Large	-0.04	-0.05	-0.04	-0.06	-0.05	-0.04	-0.05	-0.05	-0.04	-0.05	-0.05	-0.04	-0.04	-0.04	**-0.04**

Table 8
Decomposition of momentum profits, 1/41 - 12/97

The table decomposes the profitablility of momentum strategies based on the lagged 12-month returns of industry and size portfolios. The momentum stategy invests $w_{it} = (1/N)\ (r_{i,t-1} - r_{m,t-1})$ in asset i, where $r_{i,t-1}$ is the asset's lagged return and $r_{m,t-1}$ is the lagged return on the equal-weighted index. Lo and MacKinlay (1990) show that the expected return on the momentum portfolio can be separated into components that depend only on the assets' autocorrelations ('Auto'), on the cross-serial correlations among the assets ('Cross'), and on the unconditional expected returns of the assets ('Means'); see Section 2 in the text. The LM standard error is estimated using the asymptotic results of Lo and MacKinlay (1990; Appendix 2). The bootstrap standard errors are estimated from simulations which generate time-series of returns under the null hypothesis that all autocorrelations and cross-serial correlations are zero. Returns are reported in percent.

	Industry portfolios				Size portfolios			
Month	Auto	Cross	Means	Total	Auto	Cross	Means	Total
1	2.585	0.247	0.138	**2.970**	5.026	-2.760	0.336	**2.602**
3	-2.810	**4.631**	0.138	**1.959**	-4.118	5.590	0.336	**1.809**
5	-3.168	**4.257**	0.137	**1.226**	-3.575	5.008	0.338	**1.770**
7	-4.056	**5.014**	0.131	**1.089**	-3.888	5.386	0.318	**1.817**
9	**-4.983**	**5.480**	0.126	**0.623**	-4.947	**6.204**	0.331	**1.587**
11	**-6.577**	**6.139**	0.121	-0.317	-5.647	**6.855**	0.347	**1.555**
13	**-7.316**	**6.369**	0.122	**-0.826**	**-6.230**	**7.260**	0.314	**1.343**
15	**-5.286**	3.983	0.119	**-1.184**	-3.390	4.292	0.315	**1.217**
17	-4.378	3.416	0.117	**-0.844**	-3.482	4.261	0.316	**1.095**
LM std error	3.936	3.757	--	0.542	6.170	5.670	--	0.766
Bootstrap	2.670	2.580	0.088	0.362	3.613	3.507	0.219	0.400

Bold implies the estimate is more than 1.645 standard errors from zero based on the bootstrap standard error.