Momentum and Autocorrelation in Stock Returns

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This article studies momentum in stock returns, focusing on the role of industry, size, and book-to-market (B/M) factors. Size and B/M portfolios exhibit momentum as strong as that in individual stocks and industries. The size and B/M portfolios are well diversified, so momentum cannot be attributed to firm- or industry-specific returns. Further, industry, size, and B/M portfolios are negatively autocorrelated and cross-serially correlated over intermediate horizons. The evidence suggests that stocks covary "too strongly" with each other. I argue that excess covariance, not underreaction, explains momentum in the portfolios.

Momentum is one of the strongest and most puzzling asset pricing anomalies. Jegadeesh and Titman (1993) show that past winners continue to outperform past losers over horizons of 3–12 months. For example, from 1965 to 1989, stocks in the top 12-month return decile beat stocks in the bottom decile by 6.8%, on average, during the subsequent six months (t-statistic $= 3.40$). Momentum is puzzling because it suggests that prices are not even weak-form efficient. For it to be rational, risk would have to increase after positive returns, contrary to the intuition that risk should actually decline. Empirically Jegadeesh and Titman find that risk adjustment tends to accentuate rather than explain momentum [see also Fama and French (1996)].

This article further studies momentum in stock returns, focusing on the role of industry, size, and book-to-market (B/M) factors. The literature generally attributes momentum to firm-specific returns. It argues that investors either underreact or belatedly overreact to firm-specific news [e.g., Jegadeesh and Titman (2001)]. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) all develop behavioral models motivated in part by the same interpretation. In this article, I show that firm-specific returns, together with the behavioral models, cannot explain a significant component of momentum.

The article reports two sets of tests. First, I explore the profitability of portfolio-based momentum strategies. Jegadeesh and Titman (1993) use individual firms in their tests; they find that the best-performing stocks in the

past continue to beat the worst-performing stocks. Moskowitz and Grinblatt (1999) find a similar pattern in industry portfolios; the best-performing industries continue to beat the worst performers. I extend these results to size, B/M, and double-sorted size-B/M portfolios (5, 10, or 15 size and B/M portfolios; 9, 16, or 25 double-sorted portfolios). Momentum in these portfolios is as strong, and in some cases stronger, than momentum in individual stocks or industries. Moreover, size and B/M momentum is distinct from industry momentum in that neither subsumes the other.

These results are informative. They show, first, that momentum is robust and pervasive. It shows up in stocks and many types of portfolios, typically with very high significance (t-statistics > 4 are common). More importantly, the evidence shows that momentum cannot be attributed solely to firm-specific returns. The size and B/M portfolios are very well diversified. For example, size deciles each contain an average of 350 stocks from 1941 to 1999, while the 16 size-B/M portfolios each contain an average of 200 stocks from 1963 to 1999. The portfolios are also diversified across industries, and their returns seem best described as "macroeconomic." These observations imply one of two things: either firm-specific returns do not explain momentum at all, or there must be multiple sources of momentum in returns. A coherent story should explain why momentum shows up in, say, individual stocks and size quintiles, but vanishes at the market level (if anything, market returns show signs of reversals). Existing behavioral models do not explain this pattern.

The second set of tests focuses on the autocorrelation patterns in returns. It is well known that momentum is not the same as positive autocorrelation: momentum is a cross-sectional result (winners beat losers), while autocorrelation is a time-series phenomenon (a stock's past and future returns are correlated). Lo and MacKinlay (1990) show that momentum might be caused by autocorrelation in returns, lead-lag relations among stocks (cross-serial correlation), or cross-sectional dispersion in unconditional means. Intuitively a stock that outperformed other stocks in the past 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 simply has a high unconditional mean relative to other stocks.

Empirically I find that lead-lag relations among stocks play an important role. The tests focus on industry, size, and B/M portfolios because autocorrelations are difficult to estimate for individual stocks. All three sets of portfolios are negatively auto- and cross-serially correlated. To be specific, I estimate the correlation between annual returns and future monthly returns for up to 18 months in the future. From 1941 to 1999, the correlation between an industry's annual return and its return two months later averages -0.005. The correlation declines steadily to -0.064 by month 10, after which it

begins to rise. The estimates for size and B/M portfolios are similar, declining to approximately −0.070 by month 10 or 11. Cross-serial correlations among portfolios are also negative and follow the same pattern. Importantly, the lead-lag effects tend to be stronger than autocorrelations, and this difference creates momentum profits.

There are two explanations for these results. We might observe momentum, together with negative autocorrelation, if investors underreact to portfolio-specific news but overreact to macroeconomic events. Second, I show that excess covariance among stocks could produce a similar result, where "excess covariance" means, loosely, that prices covary more strongly than dividends. I present two models to illustrate how excess covariance can generate momentum. In the first model, investors mistakenly believe that news about one firm contains information about other firms. Prices covary more than they would if investors understood that news is firm specific. In the second model, prices covary too strongly because of fluctuations in the market risk premium. In both cases, momentum profits can be positive even though returns are negatively autocorrelated.

It is difficult to distinguish among these explanations. For example, they all predict that cross-serial correlations will be negative, but that portfolio-specific returns will be persistent (consistent with the evidence). I argue, however, that portfolio-specific underreaction does not explain size and B/M momentum. Most simply, it seems unlikely that investors would underreact to size- or B/M-related news, but overreact to market news. I emphasize, again, that the size and B/M portfolios are quite broad—5, 10, or 15 portfolios. News about these portfolios, like news about the overall market, is appropriately defined as macroeconomic. Thus a story in which investors react differently to idiosyncratic and macroeconomic news cannot explain the evidence. Instead, a model needs to explain why investors underreact to one type of macroeconomic news, but not another. That combination seems unlikely to me, and no behavior model predicts it.

Empirically the autocorrelation patterns in returns are inconsistent with portfolio-specific underreaction. Focusing on size quintiles, the large-stock portfolio has the least "idiosyncratic" risk. The underreaction story suggests therefore that it should be the most negatively autocorrelated, yet quintile 5's autocorrelation is actually the second closest to zero. Moreover, the lead-lag relations among large and small stocks are too large to be explained by market reversals. Finally, I show that the Fama and French (1993) three-factor model absorbs much of the serial correlation in size and B/M portfolios (but not industries). Overall the evidence suggests that excess covariance among portfolios explains industry, size, and B/M momentum.

The remainder of the article is organized as follows. Section 1 establishes some basic results on momentum. Section 2 presents several models of momentum, emphasizing the potential role of excess covariance among stocks. Section 3 explores the autocorrelation and cross-serial correlation patterns in returns. Section 4 concludes.

1. Momentum in Stock Returns

I begin, in this section, with some basic empirical results on momentum. I estimate profits using individual stocks, industries, and size and B/M portfolios.

1.1 Data

The tests use all NYSE, AMEX, and Nasdaq common stocks on the Center for Research in Security Prices (CRSP) database. The B/M portfolios require accounting data, so they are restricted to stocks on Compustat (the full CRSP sample is used for all other tests). The analysis considers the period 1941–1999, although Compustat restricts B/M portfolios to May 1963–December 1999. I exclude the pre-1941 data primarily to avoid the Depression era. Also, Jegadeesh and Titman (1993) find that momentum is negligible, or even negative, from 1927 to 1940. (Including the earlier data does not alter the conclusions.)

For tests with individual stocks, firms must have 12 months of past returns (no restriction is placed on survival going forward). I also form industry, size, B/M, and double-sorted size-B/M portfolios. Moskowitz and Grinblatt (1999) argue that momentum can be traced to industry factors. I use size and B/M portfolios because there is much evidence that they capture risk factors in earnings and returns [e.g., Fama and French (1993, 1995)].

The portfolios are constructed as follows. I calculate monthly returns for 15 industry portfolios, 5, 10, or 15 size and B/M portfolios, and 9, 16, or 25 size-B/M portfolios. Industries are based on two-digit SIC codes as reported by CRSP; they typically contain firms in consecutive two-digit codes, but some exceptions were made. Size portfolios are based on the market value of equity in the previous month. B/M portfolios are based on the ratio of book equity in the previous fiscal year to market equity in the previous month. Book values are updated four months after the fiscal year, and to reduce selection biases in Compustat, firms must have three years of accounting data before they are included in the B/M portfolios [see Kothari, Shanken, and Sloan (1995)]. Following Fama and French (1993), the breakpoints for size and B/M portfolios are determined by equally spaced NYSE percentiles. I report some tests using both equal- and value-weighted portfolios, but the majority of the article focuses on value-weighted portfolios.

Table 1 reports summary statistics for the portfolios. For brevity, it shows only the industry portfolios, size deciles, and 16 size-B/M portfolios. The table reveals two important facts. First, there is considerable cross-sectional variation in the portfolios. Average monthly returns range from 0.99% to 1.39% for the industries, 1.06% to 1.48% for the size portfolios, and 0.92% to 1.59% for the size-B/M portfolios. Standard deviations range from 3.46% for utilities up to 7.22% for small, low-B/M stocks. Second, the portfolios are quite well diversified. The average number of stocks in an industry is 231, in a size decile is 347, and in a size-B/M portfolio is 199. All but

Table 1
Summary statistics, 1941–1999

	Industry portfolios			Size portfolios			Size-B/M portfolios[a]		
Portfolio	Average return	Std. dev.	Average no. of firms	Portfolio	Average return	Std. dev.	Average no. of firms	Portfolio	Average return	Std. dev.	Average no. of firms
Natural resources	0.99	5.44	195	Small	1.48	6.78	1,557	Small: Low	1.11	7.22	474
Construction	1.00	5.08	287	2	1.29	5.83	387	2	1.17	6.10	353
Food, tobacco	1.13	4.11	120	3	1.27	5.59	286	3	1.33	5.62	393
Construction products	1.10	5.09	215	4	1.27	5.33	241	High	1.48	6.00	770
Logging, paper	1.20	5.33	65	5	1.26	5.12	210	2: Low	1.22	6.58	170
Chemicals	1.12	4.53	171	6	1.21	4.97	181	2	1.05	5.42	130
Petroleum	1.26	4.89	36	7	1.20	4.81	167	3	1.36	4.80	127
Machinery	1.20	5.29	215	8	1.23	4.62	155	High	1.59	5.64	94
Electrical equipment	1.22	5.33	370	9	1.15	4.37	145	3: Low	1.04	5.69	134
Transport equipment	1.13	5.23	97	Large	1.06	3.97	139	2	1.02	4.90	102
Shipping	1.02	5.58	101					3	1.28	4.77	84
Utilities, telecom.	1.00	3.46	203					High	1.47	5.48	48
Trade	1.14	4.91	340					Large: Low	1.06	4.70	127
Financial	1.18	4.69	601					2	0.92	4.26	81
Services, other	1.39	6.08	457					3	1.11	4.19	63
								High	1.35	5.02	30

Each month from January 1941 through December 1999, 15 industry and 10 size portfolios are formed from all NYSE, AMEX, and Nasdaq stocks classified as ordinary common equity on CRSP. Size-B/M portfolios are formed from the subset of stocks with Compustat data, from May 1963 through December 1999. The industry portfolios are based on two-digit SIC codes; they typically, but not always, consist of firms in consecutive SIC codes. The size breakpoints are determined by NYSE deciles and the size-B/M breakpoints and the size-B/M breakpoints are determined by NYSE quartiles (using independent size and B/M sorts). The table reports the average return, standard deviation, and average number of firms for each portfolio. Returns are value weighted and measured in percent.

[a] Statistics for May 1963–December 1999.

537

three portfolios average more than 63 stocks and most have more than 100. Also, many tests will use portfolios divided less finely (e.g., size and B/M quintiles), which are even better diversified. Firm-specific factors should not be important for these portfolios.

1.2 Momentum profits

To test for momentum, I form portfolios that buy winners and sell losers. Jegadeesh and Titman (1993) focus on decile-based strategies, which buy the top 10% of firms and sell the bottom 10%. I consider, instead, strategies that hold assets in proportion to their market-adjusted returns. Specifically, an asset's weight in month t is

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

where $r^k_{i,t-1}$ equals the asset's k-month return ending in $t-1$, $r^k_{m,t-1}$ equals the corresponding return on the equal-weighted index, and N is the total number of stocks. This portfolio invests most heavily in stocks with the highest past returns, but any asset that performed above average is given positive weight. Since m is the equal-weighted index, it is easy to show that the weights sum to zero. To ease the interpretation of the results, the tables report profits for a rescaled version of the portfolio that invests $1 long and $1 short every month.

The portfolio defined by Equation (1) is more convenient than a decile-based strategy for two reasons. First, the portfolio invests in all assets, not just the extremes. This makes it easier to apply the strategy to industry, size, and B/M portfolios, which consist of anywhere from 5 to 25 portfolios. Second, Lo and MacKinlay (1990) show that profits from this strategy can be easily tied to the autocorrelation of returns, a fact that I will use later.

Table 2 reports momentum profits using the different sets of portfolios. The strategies are based on past 12-month returns. Jegadeesh and Titman (1993) show that, for individual stocks, strategies based on 3- to 12-month returns are profitable. In preliminary tests I found momentum in both 6- and 12-month returns, and I focus on 12-month returns for simplicity. The table shows profits for up to 18 months after formation. The table reports only the odd months, 1, 3, 5, etc., but the discussion will sometimes refer to the ·missing months.

Momentum is strong in both individual stocks and portfolios. The results for stocks and industries are consistent with Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999): momentum is significant for 7–9 months after formation, but quickly diminishes and turns to contrarian profits. Over the first 6 months, the cumulative profit from individual stocks is 3.55% per dollar long (t-statistic $= 4.02$). This compares with 3.04% for value-weighted

Table 2
Momentum profits, 1941–1999

					Month after formation				
Assets	1	3	5	7	9	11	13	15	17
Individual stocks									
Average return	**0.500**	**0.800**	**0.451**	0.098	−0.133	**−0.333**	**−0.534**	**−0.484**	**−0.508**
t-statistic	3.08	5.03	3.06	0.72	−1.02	−2.61	−4.14	−3.84	−4.51
15 industry portfolios									
VW Average return	**0.741**	**0.497**	**0.382**	**0.327**	**0.185**	0.023	−0.093	**−0.198**	−0.138
t-statistic	6.62	4.39	3.43	3.07	1.71	0.22	−0.91	−2.00	−1.43
EW Average return	**1.005**	**0.626**	**0.409**	**0.249**	0.077	−0.109	**−0.276**	**−0.328**	**−0.291**
t-statistic	8.76	5.47	3.68	2.34	0.70	−1.01	−2.66	−3.30	−3.01
5 size portfolios									
VW Average return	**0.509**	**0.341**	**0.462**	**0.446**	**0.296**	**0.212**	**0.236**	**0.310**	**0.288**
t-statistic	4.65	2.95	4.08	4.06	2.59	1.88	2.18	2.85	2.64
EW Average return	**0.597**	**0.404**	**0.525**	**0.472**	**0.303**	**0.241**	**0.273**	**0.324**	**0.299**
t-statistic	4.77	3.05	4.03	3.74	2.33	1.85	2.26	2.63	2.40
15 size portfolios									
VW Average return	**0.505**	**0.393**	**0.422**	**0.405**	**0.297**	**0.193**	**0.217**	**0.274**	**0.209**
t-statistic	4.47	3.21	3.66	3.82	2.66	1.65	2.09	2.76	2.05
EW Average return	**0.635**	**0.499**	**0.537**	**0.512**	**0.403**	**0.266**	**0.275**	**0.335**	**0.278**
t-statistic	4.60	3.35	3.81	3.94	3.22	2.03	2.29	2.79	2.38
5 B/M portfolios[a]									
VW Average return	**0.419**	**0.456**	**0.397**	**0.347**	**0.268**	**0.263**	0.070	0.156	0.168
t-statistic	3.22	3.40	3.07	2.73	2.08	2.12	0.60	1.24	1.36
EW Average return	**0.822**	**0.684**	**0.604**	**0.626**	**0.569**	**0.465**	**0.247**	**0.313**	**0.424**
t-statistic	6.49	5.36	4.63	4.82	4.30	3.66	1.91	2.44	3.37
10 B/M portfolios[a]									
VW Average return	**0.434**	**0.382**	**0.330**	**0.272**	0.184	**0.223**	0.076	0.165	0.154
t-statistic	3.54	2.98	2.64	2.16	1.43	1.76	0.68	1.38	1.31
EW Average return	**0.925**	**0.765**	**0.673**	**0.692**	**0.622**	**0.517**	**0.286**	**0.370**	**0.471**
t-statistic	7.08	5.71	5.09	5.18	4.54	4.10	2.34	2.92	3.88
9 size-B/M portfolios[a]									
VW Average return	**0.807**	**0.570**	**0.446**	**0.529**	**0.432**	0.215	0.059	0.159	0.186
t-statistic	5.47	3.81	3.02	3.65	3.00	1.55	0.41	1.10	1.31
EW Average return	.0.977	**0.694**	**0.587**	**0.687**	**0.638**	**0.413**	0.238	**0.319**	**0.350**
t-statistic	6.33	4.56	3.98	4.81	4.57	2.87	1.60	2.18	2.39
25 size-B/M portfolios[a]									
VW Average return	**0.799**	**0.542**	**0.381**	**0.438**	**0.357**	0.150	−0.024	0.047	0.100
t-statistic	5.60	3.84	2.86	3.29	2.74	1.17	−0.18	0.37	0.77
EW Average return	**0.923**	**0.626**	**0.501**	**0.573**	**0.492**	**0.275**	0.081	0.155	0.215
t-statistic	6.22	4.34	3.69	4.28	3.78	2.06	0.59	1.16	1.59

The table reports profits for momentum strategies based on past 12-month returns. The strategies use either individual stocks or portfolios sorted by industry, size, and book-to-market (equal- or value-weighted, as indicated in the table). The strategies invest $w_{it} = (1/N)(r_{i,\,t-1} - r_{m,\,t-1})$ in asset i, where $r_{i,\,t-1} - r_{m,\,t-1}$ is the asset's lagged return in excess of the equal-weighted index; the weights are rescaled to have $1 long and $1 short. The tests use all NYSE, AMEX, and Nasdaq stocks with the necessary return and accounting data. Returns are measured in percent. Bold denotes average returns greater than 1.645 standard errors from zero.

[a] Statistics for May 1963–December 1999.

and 3.65% for equal-weighted industries (*t*-statistics = 4.75 and 5.62, respectively).[1]

The results for size and B/M portfolios are new. Profits for these portfolios are as strong, and in some instances stronger, than those from individual stocks or industries. Over the first 6 months, the cumulative profit from

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[1] The table reports profits in each month, not cumulative returns. The *t*-statistics mentioned in the text for cumulative returns are calculated using the rolling-portfolio approach of Jegadeesh and Titman (1993, p. 68).

value-weighted size quintiles is 2.56%, from value-weighted B/M deciles is 2.14%, and from 25 value-weighted size-B/M portfolios is 3.23% (t-statistics $= 4.16$, 2.99, and 4.18, respectively).[2] In all cases, profits are larger for equal-weighted portfolios, with corresponding estimates of 3.02%, 4.61%, and 3.93% (t-statistics $= 4.16$, 5.97, and 4.93). The estimates imply large Sharpe ratios, equal to the t-statistics divided by $\sqrt{T}$. In the full sample, a t-statistic of 4 implies a Sharpe ratio of 0.15, and in the truncated sample, it implies a Sharpe ratio of 0.19 (compared with 0.18 for the CRSP value-weighted index from 1941 to 1999). The table also shows that profits decay quite slowly, often remaining significant for the full 18 months. That contrasts with reversals after a year for individual stocks and industries.

Previous studies attribute momentum to firm-specific returns [e.g., Jegadeesh and Titman (1993), Grundy and Martin (2001)]. However, that cannot explain the results for size and B/M portfolios. (Industry momentum is difficult to classify: industry returns are not "firm-specific," yet they might still be described as "idiosyncratic.") As mentioned earlier, the size and B/M portfolios are quite well diversified, typically containing more than 100 stocks. Further, Table 2 shows that using broader portfolios has almost no effect on profits: the estimates from 5 size portfolios are similar to those from 15, the estimates from 5 B/M portfolios are similar to those from 10, and the estimates from 9 double-sorted portfolios are similar to those from 25. These portfolios should contain little idiosyncratic risk, so it seems likely that macroeconomic factors, not firm-specific news, explain their momentum.

Table 3 further explores the connection between firm, industry, and size-B/M momentum. The bottom line is that each appears to be distinct. Specifically, I repeat the tests in Table 2, but now report benchmark-adjusted profits in place of raw profits. For individual stocks, momentum is adjusted for industry, size, or size-B/M effects: every stock is matched either to its industry, size decile, or size-B/M quintile (5×5 sort), and momentum profits are then estimated using returns in excess of the benchmark. For industry momentum, each stock is matched to its size decile or size-B/M quintile before forming the industries. The industry return is then the average of size- or size-B/M-adjusted returns for stocks in that industry. Similarly, for size and B/M portfolios, each stock is matched to its industry before calculating returns for the portfolio.

The table shows that, in every case, profits are similar to the raw returns in Table 2. For individual stocks, industry-adjusted profits equal 2.90% (t-statistic $= 3.71$) and size-B/M-adjusted profits equal 3.69% (t-statistic $= 4.69$) over the first 6 months. These compare with 3.55% for raw returns. [The results for industry-adjusted returns are consistent with the 12-month results

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[2] The estimates for B/M and size-B/M portfolios are based on a shorter time period, May 1963–December 1999. This tends to handicap their t-statistics relative to those from the full sample.

Table 3
Benchmark-adjusted profits, 1941–1999

Assets		Month after formation								
		1	3	5	7	9	11	13	15	17
Individual stocks—industry-adjusted returns										
	Average return	**0.317**	**0.694**	**0.374**	0.069	−0.127	**−0.273**	**−0.438**	**−0.379**	**−0.419**
	t-statistic	2.18	4.90	2.86	0.57	−1.10	−2.41	−3.78	−3.34	−4.10
Individual stocks—size-adjusted returns										
	Average return	**0.406**	**0.737**	**0.391**	0.055	−0.152	**−0.349**	**−0.533**	**−0.489**	**−0.501**
	t-statistic	2.86	5.48	3.12	0.49	−1.42	−3.40	−5.23	−4.85	−5.47
Individual stocks—size and B/M-adjusted returns[a]										
	Average return	**0.537**	**0.810**	**0.456**	0.177	−0.018	**−0.258**	**−0.475**	**−0.409**	**−0.434**
	t-statistic	3.51	5.70	3.46	1.48	−0.16	−2.29	−4.25	−3.60	−4.09
15 industry portfolios—size-adjusted returns										
VW	Average return	**0.660**	**0.443**	**0.331**	**0.274**	0.154	0.003	−0.103	**−0.210**	−0.146
	t-statistic	6.37	4.22	3.20	2.75	1.53	0.03	−1.08	−2.27	−1.63
EW	Average return	**0.900**	**0.553**	**0.344**	**0.197**	0.042	−0.136	**−0.278**	**−0.327**	**−0.281**
	t-statistic	8.51	5.28	3.35	1.99	0.42	−1.37	−2.93	−3.59	−3.19
15 industry portfolios—size and B/M-adjusted returns[a]										
VW	Average return	**0.567**	**0.396**	**0.304**	**0.382**	0.212	0.060	−0.055	−0.169	−0.125
	t-statistic	4.31	2.94	2.28	3.00	1.67	0.50	−0.46	−1.44	−1.10
EW	Average return	**0.848**	**0.534**	**0.366**	**0.321**	0.189	0.001	−0.185	**−0.258**	−0.208
	t-statistic	6.55	4.27	3.00	2.70	1.54	0.01	−1.59	−2.28	−1.84
5 size portfolios—industry-adjusted returns										
VW	Average return	**0.453**	**0.304**	**0.406**	**0.390**	**0.279**	**0.197**	**0.212**	**0.277**	**0.247**
	t-statistic	4.72	3.02	4.10	4.06	2.80	2.00	2.27	2.95	2.60
EW	Average return	**0.477**	**0.322**	**0.435**	**0.408**	**0.280**	**0.221**	**0.245**	**0.301**	**0.266**
	t-statistic	4.43	2.85	3.91	3.76	2.51	1.97	2.37	2.82	2.47
15 size portfolios—industry-adjusted returns										
VW	Average return	**0.454**	**0.363**	**0.386**	**0.382**	**0.293**	**0.200**	**0.218**	**0.265**	**0.197**
	t-statistic	4.38	3.23	3.66	3.94	2.87	1.86	2.33	2.95	2.15
EW	Average return	**0.517**	**0.415**	**0.456**	**0.453**	**0.368**	**0.253**	**0.262**	**0.318**	**0.257**
	t-statistic	4.37	3.26	3.75	4.00	3.37	2.23	2.53	3.03	2.55
9 size-B/M portfolios—industry-adjusted returns[a]										
VW	Average return	**0.712**	**0.495**	**0.391**	**0.434**	**0.386**	**0.217**	0.094	**0.198**	**0.223**
	t-statistic	6.25	4.29	3.41	3.85	3.42	1.93	0.83	1.77	2.03
EW	Average return	**0.798**	**0.598**	**0.528**	**0.604**	**0.581**	**0.419**	**0.315**	**0.397**	**0.407**
	t-statistic	6.72	5.17	4.70	5.48	5.31	3.69	2.67	3.46	3.52
25 size-B/M portfolios—industry-adjusted returns[a]										
VW	Average return	**0.711**	**0.486**	**0.351**	**0.374**	**0.320**	0.151	0.028	0.105	0.151
	t-statistic	6.41	4.42	3.31	3.54	3.08	1.43	0.27	1.02	1.47
EW	Average return	**0.780**	**0.557**	**0.482**	**0.561**	**0.505**	**0.349**	**0.250**	**0.328**	**0.343**
	t-statistic	6.71	4.89	4.38	5.15	4.66	3.12	2.19	2.97	3.08

The table reports benchmark-adjusted profits for momentum strategies based on past 12-month returns. The strategies are the same as those in Table 2 (using identical weights). For individual stocks, benchmark returns are determined by the stock's industry, size, or size-B/M grouping (the size grouping is based on NYSE deciles and the size-B/M grouping is based on NYSE quintiles). The benchmark for industry portfolios is determined by the size and B/M characteristics of firms in the industry. The benchmark for size and size-B/M portfolios is determined by the industrial mix of firms in the portfolio. The tests use all NYSE, AMEX, and Nasdaq stocks with the necessary return and accounting data. Returns are measured in percent. Bold denotes average returns greater than 1.645 standard errors from zero.

[a] Statistics for May 1963–December 1999.

of Moskowitz and Grinblatt (1999).][3] Similarly industry momentum seems to be distinct from size and size-BM momentum. The benchmark-adjusted profits from any of the portfolio-based strategies have about the same magnitude, and follow the same patterns, as the raw profits in Table 2. The statistical

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[3] Note, again, that size- and B/M-adjusted profits are estimated from a shorter time period, May 1963–December 1999. Momentum profits are remarkably stable before and after 1963, so comparison across time periods poses no difficulty (within sample comparisons are similar).

significance of industry momentum drops slightly compared with Table 2, while the significance of size and B/M momentum actually goes up.

The evidence in Tables 2 and 3 suggests that momentum is a pervasive feature of returns. It shows up, separately and quite strongly, in individual stocks, industries, and size and B/M portfolios. Perhaps more importantly, momentum appears to be both a micro- and macroeconomic phenomenon. The macroeconomic component is, to my knowledge, new to this article.[4] The results suggest two possibilities: either the standard explanation for momentum, which attributes it to firm-specific returns, is wrong, or there are multiple sources of momentum in returns. Distinguishing between these possibilities is difficult. The remainder of the article will focus on the macroeconomic component, but I will offer several explanations that might apply to both firm and portfolio momentum. Ultimately, however, the article will have little to say directly about individual-stock momentum.

2. Sources of Momentum

The evidence above suggests that firm-specific returns do not fully explain momentum. This section discusses in more detail the potential sources of momentum. I present several models that generate momentum in quite different ways. The models illustrate a range of price behavior, but they are not meant to be entirely accurate descriptions of stock prices, nor to span all the possible sources of momentum.

2.1 Framework
It is useful to begin with a general framework for thinking about momentum. I follow the approach of Lo and MacKinlay (1990), who emphasize that profits depend on both autocorrelations and the lead-lag relations among stocks.

For simplicity, the analysis focuses on one-period returns (the results are easily adapted to multiple-period returns; see footnote 5). I am interested in a momentum portfolio like the one used in Section 1. Specifically, the portfolio weight of asset i in month t equals

$$w_{i,t} = \frac{1}{N}(r_{i,t-1} - r_{m,t-1}), \qquad (2)$$

where $r_{i,t-1}$ is the asset's return in month $t-1$ and $r_{m,t-1}$ is the return on the equal-weighted index in month $t-1$. Profits for this portfolio can be easily tied to the autocorrelation and cross-serial correlation of returns. Assume

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[4] Several recent articles also explore macroeconomic aspects of momentum. Chordia and Shivakumar (2001) argue that momentum can be explained by time variation in expected returns across the business cycle. Asness, Liew, and Stevens (1997) and Bhojraj and Swaminathan (2001) find momentum in international stock indices.

that returns have unconditional mean $\mu \equiv E[r_t]$ and autocovariance matrix $\Omega \equiv E[(r_{t-1} - \mu)(r_t - \mu)']$. The portfolio return in month t equals

$$\pi_t = \sum_i w_{i,t} r_{i,t} = \frac{1}{N} \sum_i (r_{i,t-1} - r_{m,t-1}) r_{i,t}, \tag{3}$$

and the expected profit is

$$E[\pi_t] = \frac{1}{N} E\left[\sum_i r_{i,t-1} r_{i,t}\right] - \frac{1}{N} E\left[r_{m,t-1} \sum_i r_{i,t}\right]$$

$$= \frac{1}{N} \sum_i (\rho_i + \mu_i^2) - (\rho_m + \mu_m^2), \tag{4}$$

where ρ_i and ρ_m are the autocovariances of asset i and the equal-weighted index, respectively. Equation (4) shows that profits depend on the magnitude of asset autocovariances relative to the market's autocovariance. In matrix notation, the average autocovariance equals $\text{tr}(\Omega)/N$ and the autocovariance of the market portfolio equals $\iota' \Omega \iota / N^2$, where $\text{tr}(\cdot)$ denotes the sum of the diagonals and ι is a vector of ones. Therefore

$$E[\pi_t] = \frac{1}{N} \text{tr}(\Omega) - \frac{1}{N^2} \iota' \Omega \iota + \sigma_\mu^2$$

$$= \frac{N-1}{N^2} \text{tr}(\Omega) - \frac{1}{N^2} [\iota' \Omega \iota - \text{tr}(\Omega)] + \sigma_\mu^2, \tag{5}$$

where σ_μ^2 is the cross-sectional variance of unconditional expected returns [collecting the μ_i and μ_m terms in Equation (4)]. The second line rearranges the first to isolate the diagonal and off-diagonal elements of Ω.[5]

This decomposition says that momentum can arise in three ways. First, stocks might be positively autocorrelated, implying that a firm with a high return today is expected to have high returns in the future. Second, cross-serial correlations might be negative, implying that a firm with a high return today predicts that *other* firms will have low returns in the future. In this case, the stock does relatively well in the future only because other stocks do poorly. (We will see below that this phenomenon is closely linked to "excess" covariance among stocks.) The third term arises because momentum strategies, by their nature, tend to buy stocks with high unconditional means: on average, stocks with the highest unconditional expected returns also have the highest realized returns. Thus profits can be positive in the absence of time-series predictability.

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[5] The tests actually consider strategies based on past 12-month returns (and held for 1–18 months). Expected profits can be decomposed in a similar manner. Suppose that annual returns have unconditional mean γ and the covariance between month $t+k$ returns and lagged 12-month returns equals $\Delta_k \equiv E[(r_t^{12} - \gamma)(r_{t+k} - \mu)']$. The expected profit in month $t+k$ is $E[\pi_{t+k}] = \text{tr}(\Delta_k)/N - \iota' \Delta_k \iota / N^2 + \sigma_{\mu\gamma}$.

The decomposition above is useful for understanding the models. I should point out, however, that it is not unique; there are alternative ways to decompose profits that suggest different roles for auto- and cross-serial correlations. Suppose, for example, that firm-specific returns are persistent, but total returns are negatively autocorrelated because of market-wide reversals. In this case, a decomposition based on firm-specific returns might lead to different conclusions than the one above. In fact, we can make a stronger observation: momentum profits are (almost) equivalent to positive autocorrelation in asset-specific returns. To see this, define the asset-specific return as the difference between the asset's return and the equal-weighted index:

$$s_{i,t} \equiv r_{i,t} - r_{m,t}.$$
(6)

Substituting into Equation (3), the expected momentum profit is

$$E[\pi_t] = \frac{1}{N}\sum_i E(s_{i,t-1}r_{i,t})$$

$$= \frac{1}{N}\sum_i \mathrm{cov}(s_{i,t-1}, s_{i,t}) + \sigma_\mu^2,$$
(7)

where the second line uses the fact that market-adjusted returns sum to zero across stocks. Ignoring σ_μ^2, this equation shows that momentum profits, by construction, equal the average autocovariance of asset-specific returns.

Notice that Equation (7) does not help us understand the source of momentum profits: any model of momentum *must* imply that asset-specific returns are positively autocorrelated. Yet we will see below that momentum can be caused by a variety of underlying price behavior. It would be wrong to look at firm-specific returns, find they are positively autocorrelated, and conclude that firm-specific underreaction explains momentum. Firm-specific returns can be persistent either because investors underreact to asset-specific news or, as the models later show, because stocks covary too strongly. These two possibilities are fundamentally different, but the decomposition in Equation (7) cannot disentangle them. I discuss these issues further in Section 3.

2.2 Basic model of stock prices
I now turn to the models. They are based on a simple 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):

$$p_t = q_t + \varepsilon_t,$$
(8)

where q_t follows a random walk and ε_t is a stationary process with mean zero. I will be more precise about how q_t and ε_t covary with each other below. The logic behind this equation is that prices follow a random walk if

expected returns are constant; time variation in expected returns implies that prices also contain a mean-reverting component.

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

$$q_t = \mu + q_{t-1} + \eta_t, \tag{9}$$

where μ is the expected drift and η_t is white noise with mean zero and covariance matrix Σ. Combining with the equation above, continuously compounded returns equal

$$r_t = p_t - p_{t-1} = \mu + \eta_t + \Delta\varepsilon_t, \tag{10}$$

where $\Delta\varepsilon_t = \varepsilon_t - \varepsilon_{t-1}$. In general, shocks to dividends and shocks to expected returns will be correlated. The vector of unconditional expected returns is $E[r_t] = \mu$.

2.3 Constant expected returns

Begin with the benchmark case in which prices follow a random walk. In terms of the model above, $\varepsilon_t = 0$ for every t. Returns are unpredictable, so first-order autocovariances are zero. Expected momentum profits from one-period returns equal

$$E[\pi_t] = \sigma_\mu^2, \tag{11}$$

where σ_μ^2 is the cross-sectional variance of expected returns. As we saw above, expected profits can be positive even without predictability because the portfolio tends to buy stocks with the highest expected returns. This effect will typically be small. Intuitively, realized returns provide an extremely noisy measure of unconditional means, so the momentum strategy chooses stocks primarily on noise in this model.

2.4 Underreaction

Momentum is typically associated with underreaction. To capture the idea that prices respond slowly to news, assume that the temporary component of prices is given by

$$\varepsilon_t = -\rho\eta_t - \rho^2\eta_{t-1} - \rho^3\eta_{t-2} - \ldots, \tag{12}$$

where $0 < \rho < 1$ and η_t represents news about dividends [see Equation (9)]. Prices deviate from a random walk because they take many periods to fully incorporate news. When information arrives, prices immediately react by

$(1-\rho)\eta_t$. After k periods, prices reflect $(1-\rho^k)$ of the news received at t. In this model, returns are given by

$$r_t = \mu + (1-\rho)\eta_t + (\rho-1)\varepsilon_{t-1}. \tag{13}$$

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

$$\text{cov}(r_t, r_{t-1}) = \left(\rho\frac{1-\rho}{1+\rho}\right)\Sigma, \tag{14}$$

where Σ is the dividend covariance matrix. Underreaction is the same for all stocks, implying that the autocovariance matrix is proportional to Σ. The expression in parentheses is positive, so autocorrelations and cross-serial correlations will typically be positive. Momentum profits can be found using Lo and MacKinlay's (1990) decomposition:

$$E[\pi_t] = \rho\frac{1-\rho}{1+\rho}\left[\frac{1}{N}\text{tr}(\Sigma) - \frac{1}{N^2}\iota'\Sigma\iota\right] + \sigma_\mu^2. \tag{15}$$

Again, the expression in brackets must be positive because Σ is a covariance matrix. Thus, underreaction leads to momentum.

2.5 Overreaction

Underreaction, along with positive autocorrelation, is the most common interpretation of momentum. Section 2.1, however, showed that lead-lag relations among stocks can also play a role. The final two models illustrate sources of cross-serial correlation in returns. Both models contain "excess" covariance among stocks: prices 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 aggregate risk premium changes over time.

Recall that prices are represented by $p_t = q_t + \varepsilon_t$, where the random walk component is $q_t = \mu + q_{t-1} + \eta_t$. To highlight the central ideas in this section, assume that shocks to dividends are completely asset specific, or $\text{cov}(\eta_t) = \sigma_\eta^2 I$, where I is an identity matrix. Investors, however, mistakenly believe that news about one asset contains information about other assets. In particular, suppose the temporary component of price equals

$$\varepsilon_t = B\eta_t + B\rho\eta_{t-1} + B\rho^2\eta_{t-2} + \cdots, \tag{16}$$

where $0 < \rho < 1$ and B is an $N \times N$ matrix with 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 information arrives, prices immediately react by $(I+B)\eta_t$. After k periods, prices reflect

$(I + \rho^{k-1} B)$ of the news received at t. We will put additional restrictions on the matrix B below, but the idea is that B determines how much stocks covary with each other.

Fluctuations around a random walk are persistent but temporary. In particular, $\varepsilon_t = \rho \varepsilon_{t-1} + B \eta_t$, and returns equal $r_t = \mu + (I + B) \eta_t + (\rho - 1) \varepsilon_{t-1}$. Returns become more volatile and negatively autocorrelated. The variance of returns equals

$$\text{cov}(r_t) = \sigma_\eta^2 \left[I + B + B' + \frac{2}{1+\rho} BB' \right], \tag{17}$$

which has positive off-diagonals, representing excess covariance. The first-order autocovariance matrix is given by

$$\text{cov}(r_t, r_{t-1}) = \sigma_\eta^2 (\rho - 1) \left[B + \frac{1}{1+\rho} BB' \right], \tag{18}$$

which is everywhere negative since $\rho < 1$ and B has only nonnegative terms. In other words, both the autocorrelations and cross-serial correlations are negative, consistent with the intuition that investors overreact to news.

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, suppose that the matrix B equals

$$B = b[\iota\iota' - I], \tag{19}$$

where b is a scalar such that $0 < b < 1$. The matrix 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. Momentum profits equal

$$E[\pi_t] = \sigma_\eta^2 \frac{b(\rho - 1)(N - 1)}{N} \left[\frac{b}{1+\rho} - 1 \right] + \sigma_\mu^2, \tag{20}$$

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

2.6 Time-varying risk premium

Overreaction is one possible source of excess covariance. Of course, stocks can also covary "too strongly" in the absence of any irrationality. In this section I assume that excess covariance is caused by time variation in the aggregate risk premium.

Recall, for the last time, the basic model: $p_t = q_t + \varepsilon_t$ and $q_t = \mu + q_{t-1} + \eta_t$. If changes in the risk premium drive temporary price movements, then all

asset prices should fluctuate together in a specific way. In particular, assume that price fluctuations around a random walk are perfectly correlated across assets, so that

$$\varepsilon_t = x_t \beta, \tag{21}$$

where x_t is a positively autocorrelated scalar with mean zero and β 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 β are positive, so expected returns move together over time. The notation β 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 capital asset pricing model (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 beta. Although I make no assumption here about the validity of the CAPM, the notation β is chosen to capture this intuition.

In this model, stocks covary "too strongly" because they are sensitive to changes in the risk premium. Returns are given by $r_t = \mu + \eta_t + \beta \Delta x_t$, where $\Delta x_t = x_t - x_{t-1}$. It seems reasonable to assume that Δx_t is positively correlated with η_t. The vector η_t measures news about dividends, while Δx_t measures the price effect of changes in the risk premium. If cash flows and the risk premium move in opposite directions, Δx_t and η_t will be positively related. This suggests, for example, that the market's expected return will be lower during expansions than recessions, consistent with empirical evidence [e.g., Fama and French (1989), Campbell (1991)].

Assume for simplicity that x_t follows an AR(1) process, $x_t = \rho x_{t-1} + \nu_t$. The covariance between innovations of the dividend process and Δx_t equals

$$\delta \equiv \mathrm{cov}(\eta_t, \Delta x_t) = \mathrm{cov}(\eta_t, \nu_t), \tag{22}$$

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

$$\mathrm{cov}(r_t) = \Sigma + \sigma_{\Delta x}^2 \beta \beta' + \beta \delta' + \delta \beta'. \tag{23}$$

Because all elements of $\mathrm{cov}(r_t)$ 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

$$\mathrm{cov}(r_t, r_{t-1}) = \rho_{\Delta x} \beta \beta' + (\rho - 1)\beta \delta', \tag{24}$$

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. Momentum profits take a particularly simple form:

$$E[\pi_t] = \rho_{\Delta x}\sigma_\beta^2 + (\rho - 1)\sigma_{\beta,\delta} + \sigma_\mu^2, \tag{25}$$

where σ_β^2 is the cross-sectional variance of β and $\sigma_{\beta,\delta}$ is the cross-sectional covariance between β and δ. This equation follows from the decomposition in Section 2.1.

To interpret Equation (25), 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. For positive profits, it must be true that stocks whose prices are sensitive to the risk premium (high β_i) have cash flows that do *not* covary strongly with the risk premium (low δ_i). This condition is plausible. Suppose, for example, that small firms are sensitive to business conditions, so their cash flows covary strongly with the risk premium (high δ_i). At the same time, we might expect that the duration of a firm's cash flows determines how sensitive its price is to movements in the risk premium. If small stocks have a shorter duration than large stocks, then movements in the risk premium would have a smaller direct effect on their value (low β_i). Under these conditions, a momentum strategy can earn positive profits. The point here is not to argue that we should expect momentum, but only to provide some intuition about the conditions that would be necessary.

2.7 Summary
The models above show that momentum can arise in a variety of ways. Underreaction is one possible source, but not the only; excess covariance can also lead to momentum. Distinguishing among the stories is difficult. Overreaction and a time-varying risk premium generate similar patterns of autocorrelations and cross-serial correlations; any attempt to disentangle these stories bumps up against Fama's (1970) joint-testing problem (it relies on an equilibrium model of returns). Even distinguishing between excess covariance and underreaction might not be easy if investors react differently to micro- and macroeconomic news. The next section shows that underreaction to asset-specific news and overreaction to macroeconomic news can generate patterns that are similar to excess covariance. Recognizing these difficulties, the remainder of the article investigates the autocorrelation patterns in returns to better understand momentum profits.

3. Autocorrelation Patterns in Returns

The models in Section 2 showed that momentum is consistent with a variety autocorrelation and cross-serial correlation patterns in returns. This section explores the patterns in detail for value-weighted industry, size, and B/M portfolios.

The earlier tests, in Section 1, considered strategies based on 12-month returns; I estimated profits for 1–18 months after the momentum portfolios

were formed. This section follows a similar approach. I test whether a portfolio's annual return is correlated with its own and other portfolios' monthly returns for up to 18 months in the future. Thus I am interested in the auto-covariance matrices $\Delta_k \equiv E[(r_t^{12} - \gamma)(r_{t+k} - \mu)']$, where μ and γ are the vectors of expected 1- and 12-month returns, and $k = 1$ to 18.

3.1 Autocorrelations

The autocorrelation matrices are too large to report for every lag. Table 4 summarizes them for the industry portfolios and the size and B/M quintiles. The table reports the average, across the 18 lags, of the autocorrelation matrices. The portfolio used as the predictive variable changes as you move down the columns and the portfolio whose return is being predicted changes as you move across the rows (see the definition of Δ_k above). Statistical significance is difficult to assess analytically, so the tests are based on bootstrap simulations. The simulations replicate the empirical tests using artificial time series of returns, constructed by sampling with replacement from the actual return series. This procedure, repeated many times, creates a sampling distribution under the null.

The results in Table 4 are striking. The autocorrelations and cross-serial correlations are almost entirely negative and often statistically significant (roughly half of the estimates). Across the three sets of portfolios, the average autocorrelation equals -0.04 and the average cross-serial correlation equals -0.05. The estimates are similar for the three sets of portfolios, although the shorter sample used for B/M portfolios (May 1963–December 1999) means that their statistical significance is lower. The standard error of the estimates, not reported in the table, is approximately 0.025 for industry and size portfolios and 0.033 for B/M portfolios.

The table reveals a number of interesting patterns. For the size portfolios, the autocorrelations are most negative for the 3rd and 4th quintiles (-0.05 and -0.07, respectively). The estimates are closer to zero for the smallest and very largest stocks. The top three quintiles are negatively correlated with the future returns on all portfolios, while the smallest stocks are negatively correlated with the future returns on quintiles 4 and 5. These lead-lag relations are quite strong, especially the predictive power of quintile 5. Statistically, no simulation out of 5,000 yields an estimate as negative as that for quintile 5 leading quintile 1.

Table 4 provides an interesting contrast with the momentum results in this and other articles. The literature suggests that momentum is one of the strongest asset pricing anomalies, while prior evidence of mean reversion in returns is weak [e.g., Fama and French (1988), Richardson (1993)]. Table 4 shows, however, that reversals, not continuations, completely dominate the autocorrelation matrices. Importantly, that observation is true for all three sets of portfolios, so it does not appear to be sensitive to the way portfolios are formed.

Table 4
Serial correlation in industry, size, and B/M portfolios, 1941–1999

Size portfolios

Past returns	$R_{Small,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{Big,t}$
$R_{Small,t-k}$	−0.02	−0.03	−0.03	**−0.05**	**−0.05**
$R_{2,t-k}$	−0.04	−0.04	−0.04	**−0.05**	**−0.05**
$R_{3,t-k}$	**−0.05**	**−0.05**	**−0.05**	**−0.06**	**−0.05**
$R_{4,t-k}$	**−0.07**	**−0.06**	**−0.06**	**−0.07**	**−0.05**
$R_{Big,t-k}$	**−0.10**	**−0.08**	**−0.07**	**−0.07**	−0.04

B/M portfolios[a]

Past returns	$R_{Low,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{High,t}$
$R_{Low,t-k}$	−0.04	**−0.07**	**−0.05**	**−0.08**	**−0.08**
$R_{2,t-k}$	−0.03	−0.04	−0.02	**−0.05**	**−0.06**
$R_{3,t-k}$	−0.04	−0.04	−0.02	**−0.05**	**−0.06**
$R_{4,t-k}$	**−0.05**	−0.03	−0.01	−0.03	−0.04
$R_{High,t-k}$	**−0.06**	−0.04	−0.02	−0.04	−0.04

Industry portfolios

Past returns	$R_{1,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{5,t}$	$R_{6,t}$	$R_{7,t}$	$R_{8,t}$	$R_{9,t}$	$R_{10,t}$	$R_{11,t}$	$R_{12,t}$	$R_{13,t}$	$R_{14,t}$	$R_{15,t}$
$R_{1,t-k}$	**−0.05**	**−0.06**	**−0.05**	**−0.07**	**−0.06**	**−0.06**	**−0.06**	**−0.08**	**−0.08**	**−0.08**	**−0.06**	**−0.07**	**−0.07**	**−0.05**	**−0.06**
$R_{2,t-k}$	−0.04	**−0.05**	**−0.05**	**−0.07**	**−0.05**	**−0.06**	−0.02	**−0.05**	**−0.06**	**−0.06**	**−0.07**	−0.03	**−0.07**	**−0.05**	**−0.07**
$R_{3,t-k}$	**−0.05**	−0.01	−0.03	**−0.05**	−0.03	−0.01	−0.01	**−0.05**	**−0.05**	−0.04	**−0.06**	−0.01	−0.03	−0.04	**−0.07**
$R_{4,t-k}$	−0.03	−0.03	−0.04	−0.04	−0.03	**−0.06**	−0.01	**−0.06**	**−0.08**	**−0.05**	**−0.08**	−0.02	**−0.05**	−0.04	−0.04
$R_{5,t-k}$	−0.04	**−0.06**	−0.03	**−0.08**	−0.04	−0.03	0.00	−0.03	−0.03	**−0.06**	**−0.06**	−0.05	**−0.08**	**−0.06**	**−0.09**
$R_{6,t-k}$	−0.04	**−0.06**	−0.04	**−0.07**	**−0.06**	−0.03	−0.05	**−0.06**	−0.03	**−0.06**	**−0.06**	−0.01	**−0.06**	**−0.06**	**−0.07**
$R_{7,t-k}$	**−0.05**	**−0.06**	−0.06	**−0.07**	**−0.05**	**−0.07**	−0.05	**−0.06**	**−0.06**	**−0.07**	**−0.08**	−0.04	**−0.07**	**−0.06**	**−0.07**
$R_{8,t-k}$	−0.04	**−0.06**	−0.03	**−0.05**	**−0.06**	**−0.06**	−0.02	**−0.08**	−0.03	**−0.07**	**−0.08**	−0.05	**−0.06**	**−0.06**	−0.04
$R_{9,t-k}$	−0.03	−0.03	−0.02	**−0.05**	−0.01	−0.07	−0.01	−0.02	−0.02	**−0.07**	**−0.06**	−0.01	**−0.05**	−0.03	−0.02
$R_{10,t-k}$	−0.03	−0.04	−0.02	**−0.05**	−0.02	−0.04	0.01	−0.02	−0.03	−0.04	−0.04	−0.01	**−0.07**	−0.03	−0.04
$R_{11,t-k}$	−0.03	−0.03	−0.04	**−0.05**	−0.04	−0.03	−0.02	−0.01	−0.02	**−0.05**	**−0.06**	−0.02	**−0.05**	**−0.05**	−0.04
$R_{12,t-k}$	**−0.05**	−0.04	−0.02	**−0.06**	−0.02	**−0.05**	−0.03	−0.01	−0.01	−0.03	**−0.06**	0.00	−0.04	**−0.07**	**−0.07**
$R_{13,t-k}$	**−0.05**	**−0.05**	−0.03	**−0.07**	−0.02	−0.03	−0.02	−0.03	−0.03	**−0.05**	**−0.07**	−0.02	**−0.06**	**−0.06**	**−0.06**
$R_{14,t-k}$	**−0.05**	**−0.05**	−0.02	**−0.07**	−0.02	−0.03	−0.02	−0.03	−0.04	−0.04	**−0.07**	−0.02	**−0.05**	**−0.05**	**−0.05**
$R_{15,t-k}$	−0.03	−0.04	−0.01	−0.04	−0.01	−0.05	−0.01	−0.02	−0.04	**−0.05**	**−0.07**	−0.03	−0.04	−0.03	−0.03

The table reports autocorrelations (diagonals) and cross-serial correlations (off diagonals) for value-weighted industry, size, and B/M portfolios. The industries appear in the same order as in Table 1. Autocorrelations equal the correlation between a portfolio's monthly return and its past 12-month return. Cross-serial correlations equal the correlation between a portfolio's monthly return and the past 12-month returns on other assets. The table reports the average correlation for lags of 1–18 months; the correlations are estimated individually for each lag and then averaged. The portfolio used as the predictive variable (12-month returns) changes as you move down the columns, and the portfolio being predicted changes as you move across the rows. Bold denotes estimates that are significant at the 5% level based on bootstrap simulations.

[a] Statistics for May 1963–December 1999.

The results are consistent with the excess-covariance models in Section 2. There is no evidence of persistence in returns, as suggested by models of underreaction. Alternatively, investors might simply underreact to portfolio-specific news but overreact to market news. Suppose, for example, that we decompose returns into $r_{i,t} = \beta_i r_{m,t} + \varepsilon_{i,t}$, where r_m is negatively autocorrelated and ε_i is positively autocorrelated. Assume, further, that r_m, ε_i, and ε_j are independent at all leads and lags ($i \neq j$). Then the autocovariance of r_i is $\rho_i = \beta_i^2 \rho_m + \rho_{\varepsilon i}$ and the cross-serial covariance between $r_{i,t}$ and $r_{j,t-1}$ is $\rho_{ij} = \beta_i \beta_j \rho_m$. Cross-serial correlations pick up the reversals in market returns, and so will be negative. Autocorrelations pick up market reversals and the persistence in ε_i; they will be negative if market reversals dominate. These predictions are similar to the models in Section 2.

Table 4 provides some guidance for distinguishing among the models. Before I discuss the evidence, it is useful to reflect on the portfolio-specific underreaction story. The intuition is that investors might react differently to idiosyncratic and market-wide news. However, I am not aware of any behavioral model that predicts this result. The recent articles by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) do not differentiate between firm-specific and market-wide news. Indeed, the authors suggest that their models apply to both. Therefore, even if we believe that portfolio-specific underreaction explains momentum, Table 4 rejects the behavioral models as a general description of prices.

There is also a serious flaw in the underreaction story: the returns for size and B/M quintiles, and to a less extent industry portfolios, cannot reasonably be described as "idiosyncratic." Recall that the size and B/M portfolios are quite broad. Further, there is much evidence that their returns capture common risk factors in returns [Fama and French (1993)]. Thus there seems little basis for predicting that investors will underreact to size- and B/M-specific news, but overreact to market news—both are macroeconomic. Notice that, in contrast, the models in Section 2 do not require that investors react differently to one type of news than another. Those models say that momentum profits and negative autocorrelation arise from the same source.

Empirically the size quintiles provide evidence against the portfolio-specific underreaction story. To see why, suppose that negative autocorrelation is driven entirely by market reversals. The autocorrelation of a portfolio should be a weighted average of the market and portfolio-specific return autocorrelations:

$$\text{cor}(r_{it}, r_{it-1}) = \lambda_i \text{cor}(r_{mt}, r_{mt-1}) + (1 - \lambda_i)\text{cor}(\varepsilon_{it}, \varepsilon_{it-1}), \qquad (26)$$

where λ_i is the squared correlation between r_i and r_m.[6] I show later that $\text{cor}(\varepsilon_{it}, \varepsilon_{it-1})$ is similar across size quintiles, so most of the variation in

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[6] $\text{Cor}(r_{it}, r_{it-1}) = \text{cov}(r_{it}, r_{it-1})/\text{var}(r_i) = (\beta_i^2 \rho_m + \rho_{\varepsilon i})/\text{var}(r_i)$, where ρ_m and $\rho_{\varepsilon i}$ are the autocovariances of market and portfolio-specific returns, respectively. Equation (26) follows by substituting $\rho_m = \text{var}(r_m) \times \text{cor}(r_{mt}, r_{mt-1})$ and $\rho_{\varepsilon i} = \text{var}(\varepsilon_i) \times \text{cor}(\varepsilon_{it}, \varepsilon_{it-1})$ in the numerator.

$cor(r_{it}, r_{it-1})$ should come from differences in λ_i. In other words, if market reversals explain negative autocorrelation, portfolios with the least "idiosyncratic" risk should be the most negatively autocorrelated. Empirically that is not true. Quintile 5 easily has the least idiosyncratic risk (λ_i varies from 0.64 for quintile 1 to 0.98 for quintile 5), yet its autocorrelation is the second closest to zero. The difference with portfolio 4 is significant at the 1.8% level.

The cross-serial correlations are also difficult to reconcile with portfolio-specific underreaction. Using the results above, if market reversals explain cross-serial covariances, the covariance between $r_{i,t}$ and $r_{j,t-1}$ is $\beta_i\beta_j\rho_M$. Collecting assets, $cov(r_{t-1}, r_t) = \beta\beta'\rho_M$, which is a matrix whose rows and columns are all proportional to the vector of market betas (ignore the diagonals). Similarly the matrix of cross-serial *correlations* should have rows that are proportional to the vector of *correlations* with the market portfolio.[7] Table 4 shows that this prediction is not true. For the size portfolios, the cross-serial correlations in the bottom row have exactly the wrong pattern; they should be closest to zero for the smallest stocks. Also, moving up the matrix, the pattern of coefficients reverses, so the rows are far from proportional to each other. The patterns for industry and B/M portfolios provide similar, but less distinct, problems for the underreaction story.

The cross-serial correlations could, in principle, be generated by either of the excess-covariance models in Section 2. Unfortunately the models are not developed precisely enough to make strong predictions about the pattern of autocorrelations and cross-serial correlations (other than the fact they should be negative). For the overreaction model, we would need to know which stocks are likely to exhibit the most excess covariance. For the time-varying risk premium model, we would need an equilibrium model of expected returns. I will provide evidence shortly using the CAPM and the Fama and French (1993) three-factor model.

3.2 Autocorrelations and the forecast horizon

The summary statistics above are informative, but they mask changes in the autocorrelation matrices across lags. Table 5 explores how the autocorrelations change as the lag increases from 1 to 18 months. Specifically I estimate the slope coefficient when a portfolio's monthly return is regressed on its lagged annual return. I focus on autocorrelations because it is not practical to report cross-serial correlations for every lag. The table shows results for size quintiles, 15 industry portfolios, and 9 double-sorted size-B/M portfolios. I now use the double-sorted portfolios, in place of B/M quintiles, because they should be more informative.

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[7] Pre- and postmultiply the covariance matrix by S^{-1}, where S is a diagonal matrix with portfolios' standard deviations on its diagonal.

Table 5
Autocorrelations, 1941–1999

Portfolio		1	3	5	7	9	11	13	15	17
					Forecast horizon (months)					
Size portfolios										
Small		**.016**	−.002	−.003	−.004	−.006	−.007	−.010	−.006	−.006
2		.007	−.010	−.008	−.009	−.013	−**.014**	−**.015**	−.007	−.008
3		.000	−.016	−.012	−.013	−**.016**	−**.018**	−**.016**	−.007	−.008
4		−.007	−**.020**	−**.017**	−**.020**	−**.022**	−**.023**	−**.020**	−.011	−.010
Big		.000	−.006	−.007	−.010	−.015	−**.018**	−**.019**	−.011	−.008
Average		.003	−.011	−.009	−.011	−**.014**	−**.016**	−**.016**	−.008	−.008
Wald test (χ^2)		**27.0**	**20.1**	**11.0**	**13.7**	**10.2**	**9.7**	5.3	3.8	2.0
Industry portfolios										
Natural resources		−.002	−.012	−.008	−.007	−.008	−**.018**	−**.019**	−**.020**	−**.018**
Construction		−.004	−.011	−.006	−.009	−**.016**	−**.022**	−**.019**	−.011	−.011
Food, tobacco		.014	.008	.005	.003	−.005	−.006	−.014	−.012	−.009
Construction products		.013	−.005	−.005	−.009	−.014	−**.016**	−**.020**	−.012	−.009
Logging, paper		−.003	−.007	−.002	−.008	−.014	−.015	−.014	−.011	−.014
Chemicals		.004	−.001	.001	−.004	−.012	−.012	−**.017**	−.014	−**.016**
Petroleum		−.001	−.003	−.008	−.009	−.014	−**.019**	−**.018**	−**.020**	−.015
Machinery		.003	−.010	−.006	−.003	−.010	−.014	−.009	.006	.003
Electrical equipment		.002	−.007	−.006	−.005	−.008	−.012	−.013	−.007	−.007
Transport equipment		.007	−.004	−.004	−.005	−.011	−**.019**	−**.017**	−.011	−.011
Shipping		−.002	−.015	−**.015**	−**.019**	−**.024**	−**.028**	−**.024**	−.013	−.008
Utilities, telecom.		.011	.006	−.002	−.011	−.009	−.012	−.011	−.003	.003
Trade		.007	−.011	−.012	−**.015**	−.012	−**.018**	−**.026**	−**.018**	−**.015**
Financial		.001	−.013	−.010	−**.015**	−**.015**	−**.017**	−**.019**	−.011	−.012
Services, other		.011	−.004	−.007	−.006	−.003	−.006	−**.013**	−.008	−.004
Average		.004	−.006	−.006	−.008	−**.012**	−**.016**	−**.017**	−**.011**	−.009
Wald test (χ^2)		13.2	16.1	10.0	14.3	11.5	14.3	14.9	17.5	15.0
Size-B/M portfolios[a]										
Small	Low	.008	−.011	−.007	−.001	−.008	−.013	−**.020**	−.009	−.005
	2	.005	−.011	−.002	.001	−.008	−.012	−.019	−.009	−.011
	High	.008	−.010	−.001	.000	−.006	−.008	−.016	−.008	−.013
Medium	Low	−.007	−**.022**	−.012	−.007	−.011	−.020	−**.022**	−.010	−.005
	2	−.006	−.016	−.004	−.006	−.009	−.014	−.016	−.003	−.005
	High	−.008	−.023	−.010	−.011	−.012	−.012	−.020	−.005	−.011
Large	Low	−.003	−.006	−.005	−.002	−.004	−.012	−.021	−.016	−.007
	2	−.008	−.006	.000	−.005	−.006	−.012	−.012	.002	.002
	High	−.006	−.019	−.007	−.010	−.012	−.018	−.019	.000	−.004
Average		−.002	−.014	−.005	−.005	−.008	−.013	−**.018**	−.006	−.007
Wald test (χ^2)		11.7	12.5	6.0	5.1	2.6	4.9	6.6	4.8	5.0

The table reports, for lags of 1–18 months, the OLS slope coefficient when a portfolio's monthly return is regressed on its own past 12-month return. The table shows estimates for value-weighted industry, size, and size-B/M portfolios, described more fully in Table 1. Bold denotes estimates that are greater than 1.645 standard errors from zero or Wald statistics that are significant at the 10% level.

[a] Statistics for May 1963–December 1999.

The autocorrelations again provide no evidence of persistence in returns, even at short horizons. The estimates are uniformly negative beyond month 1.[8] Statistically they are most reliably negative for industry and size portfolios, which is not surprising given that the sample is much shorter for the size-B/M portfolios. (The standard errors cluster between 0.0085 and 0.0095

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[8] The anomalous results for month 1 are probably explained by the lead-lag relations in weekly returns documented by Lo and MacKinlay (1990). Jegadeesh and Titman (1995) argue that the weekly lead-lag patterns have little effect on momentum profits.

for industry and size portfolios and between 0.012 and 0.014 for size-B/M portfolios.) Interestingly, the estimates decline for about a year. For the size portfolios, the average is −0.007 in month 2, dropping to −0.019 by month 10 (standard errors of 0.008). The average is more than 1.75 standard errors below zero in months 8–13. Similarly, for industry portfolios, the average autocorrelation in month 2 is −0.003 and reaches a minimum of −0.017 in month 10 (standard errors of 0.007). The estimates are again more than 1.75 standard errors from zero in months 8–14. The U-shaped pattern in autocorrelations is not reflected in momentum profits, which decline steadily as the forecast horizon increases (see Table 2).[9]

Economically the estimates imply significant time variation in expected returns. Annual returns typically have a standard deviation between 20% and 25%. Therefore a two standard deviation increase in annual returns implies a 40—50 basis point drop in future returns if the slope is −0.01. Many of the estimates are this large. For the average size portfolio, the cumulative slope coefficient over 6 months is −0.043 and over 12 months is −0.135. The corresponding estimates are −0.023 and −0.104 for industry portfolios −0.044 and −0.112 for size-B/M portfolios. The implied changes in expected returns appear to be economically large.

3.3 Autocorrelations and momentum profits
From the evidence above, it is clear that persistence in returns does not explain momentum. Table 6 shows this formally using Lo and MacKinlay's (1990) decomposition. Recall from Section 2.1 that expected momentum profits equal

$$E[\pi_{t+k}] = \frac{N-1}{N^2}\text{tr}(\Delta_k) - \frac{1}{N^2}[\iota'\Delta_k\iota - \text{tr}(\Delta_k)] + \sigma_{\mu,\gamma}, \qquad (27)$$

where Δ_k is the covariance between r_{t+k} and r_t^{12}, and $\sigma_{\mu,\gamma}$ is the cross-sectional covariance between expected 1- and 12-month returns. The first term depends on autocorrelations ("Auto" in the table), the second term depends on cross-serial correlations ("Cross"), and the last term picks up the effects of cross-sectional dispersion in unconditional means ("Means").

The standard errors require some explanation. For simplicity the table reports only the average standard error across the 18 lags. This is innocuous because the standard errors should all be the same (except that the sample sizes differ slightly). More importantly, the table shows two sets of estimates. The first set, "LM std error," is based on the asymptotic results of Lo and

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[9] The slope estimates in these regressions are biased downward, but the bias is small and cannot explain the results. For the full sample, the bias is approximately −0.002 based on bootstrap simulations. Lewellen (2001) explores the patterns in greater detail.

Table 6
Decomposition of momentum profits, 1941–1999

Month	Industry portfolios				5 size portfolios				9 size-B/M portfolios[a]			
	Auto	Cross	Means	Total	Auto	Cross	Means	Total	Auto	Cross	Means	Total
1	2.49	0.85	0.15	**3.49**	3.08	−1.28	0.13	**1.93**	−0.09	2.72	0.42	**3.05**
3	−2.51	**4.80**	0.14	**2.43**	−3.99	**5.11**	0.13	**1.25**	−5.35	**6.75**	0.42	**1.83**
5	−2.59	4.18	0.14	**1.73**	−3.27	4.51	0.14	**1.37**	−2.18	3.49	0.43	**1.74**
7	−2.99	**4.34**	0.13	**1.48**	−3.26	4.53	0.12	**1.39**	−1.47	3.05	**0.43**	**2.01**
9	−4.22	**5.08**	0.13	**0.99**	−4.87	**5.87**	0.13	**1.14**	−3.35	4.38	**0.45**	**1.48**
11	**−5.91**	**5.92**	0.12	0.13	**−5.33**	**6.32**	0.14	**1.13**	−5.27	5.83	**0.45**	**1.02**
13	**−6.70**	**5.92**	0.12	−0.66	**−5.52**	**6.29**	0.13	**0.90**	−7.39	**7.11**	**0.45**	0.18
15	**−4.57**	3.42	0.12	**−1.03**	−3.02	3.79	0.13	**0.90**	−2.89	2.99	**0.47**	0.57
17	−3.88	3.12	0.11	−0.65	−3.09	3.73	0.14	**0.79**	−2.88	3.08	**0.47**	0.66
LM SE	3.84	3.68	—	0.61	4.57	4.29	—	0.50	5.80	5.54	—	0.68
Bootstrap SE	2.66	2.56	0.11	0.37	2.93	2.84	0.14	0.33	4.15	3.99	0.26	0.56

The table reports total profits, along with the Lo and MacKinlay (1990) decomposition, for momentum strategies based on past 12-month returns. The strategies invest $w_{it} = (1/N)(r_{i,t-1} - r_{m,t-1})$ in asset i, where $r_{i,t-1} - r_{m,t-1}$ is the asset's lagged return in excess of the equal-weighted index. Auto is the component of profit attributed to autocorrelation, Cross is the component attributed to cross-serial correlation, and Means is the component attributed to unconditional expected returns. The LM standard error is based on the asymptotic results of Lo and MacKinlay and the bootstrap standard error is estimated from simulations. Returns are measured in percent. Bold denotes estimates that are more than 1.645 standard errors from zero based on the bootstrap simulations.
[a] Statistics for May 1963–December 1999.

MacKinlay (1990, Appendix 2). The second set is based on bootstrap simulations, similar to those described earlier. The discussion below focuses on the bootstrap estimates.[10]

The table confirms the earlier results. Autocorrelations are always negative after month 1, and therefore reduce momentum profits. (The magnitudes are difficult to interpret because the size of the long-short position changes over time; see Table 2 for a rescaled portfolio that invests $1 long and $1 short every month.) For the industry portfolios, the autocovariance component of profits equals −2.51 (*t*-statistic = −0.94) in month 3 and declines to −6.70 (*t*-statistic = −2.52) in month 13. In comparison, the cross-serial component equals 4.80 (*t*-statistic = 1.87) in month 3 and rises to 6.87 (*t*-statistic = 2.68) in month 10. Total profits decline because cross-serial correlations do not fully offset changes in autocorrelations. Size and size-B/M portfolios show a similar pattern, but autocorrelations drop more slowly and total profits remain positive.[11]

Cross-sectional variation in expected returns has only a small effect on profits. For the industry portfolios, unconditional expected returns contribute

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[10] Surprisingly, the bootstrap standard errors are smaller than the LM estimates. I do not have a good explanation for the difference. One possibility is that the LM standard errors are consistent even when returns are serially correlated; the bootstrap standard errors are accurate only under the null. As a robustness check, I repeated the simulations allowing for heteroscedasticity [the equal-weighted index follows a GARCH(1,1) process and the volatility of all stocks moves together]. The standard errors from these simulations are quite similar to those from the i.i.d. simulations, with less than a 5% change in the estimates.

[11] The decomposition suffers from a small-sample bias because autocorrelations and cross-serial correlations are biased downward. Simulations suggest that the bias is relatively small. The bias in the autocovariance component is approximately −0.50 for industry and size portfolios and −0.77 for size-B/M portfolios. The corresponding biases in the cross-serial covariance components are approximately 0.41 and 0.66, respectively.

between 0.11 and 0.15 to momentum profits. To put these in perspective, total profits range from 3.49 to −1.03. The evidence is similar for size and B/M portfolios (the double-sorted portfolios suggest a somewhat larger role for unconditional means). These results are opposite those of Conrad and Kaul (1998). Conrad and Kaul argue that unconditional expected returns are the most important source of profits. However, their conclusions are based on individual stock returns, and it seems likely that noise in the estimates drives their results. Jegadeesh and Titman (2001) discuss Conrad and Kaul's methodology in detail.

3.4 Market-adjusted returns

The analysis so far provides two facts about market-adjusted returns: (1) momentum is equivalent to persistence in market-adjusted returns (Section 2.1), and (2) the lead-lag relations among stocks are not fully explained by reversals in market returns (Section 3.1). The first observation implies that market-adjusted returns must be positively autocorrelated, but that does not help distinguish between competing models. The second observation suggests that market-adjusted returns will exhibit interesting lead-lag patterns. Table 7 looks specifically at the predictability of market-adjusted returns, defined simply as the difference between the portfolio's return and the CRSP value-weighted index (the results are similar if I adjust for beta).

The table shows, not surprisingly, that market-adjusted returns are positively autocorrelated. The estimates are highly significant for all three sets of portfolios. The average autocorrelation equals 0.08 for size portfolios, 0.06 for B/M portfolios, and 0.02 for industry portfolios.[12] The size quintiles show no clear pattern across portfolios, but the estimate is largest for quintile 1. The pattern is clearer for B/M portfolios, with autocorrelations greatest for high B/M stocks.

The cross-serial correlations are also strong. For the most part, the patterns reflect the contemporaneous correlation among portfolios. Boudoukh, Richardson, and Whitelaw (1994) show that the lead-lag relation between two portfolios, i and j, should depend on their contemporaneous correlation: $\mathrm{cor}(r_{i,t-1}, r_{j,t}) = \mathrm{cor}(r_{j,t-1}, r_{j,t}) \times \mathrm{cor}(r_{i,t}, r_{j,t})$. This result, which also applies to market-adjusted returns, holds if $r_{i,t-1}$ does not contain incremental information about $r_{j,t}$ beyond j's own past return. Without showing the details, the cross-serial correlations are generally, but not always, consistent with this prediction. (For a counterexample, note that the cross-serial correlations in a given *column* should always be less than autocorrelation in that *column*. This restriction is sometimes grossly violated; e.g., B/M quintiles 2 and 3 or industries 9, 13–15.)

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[12] The autocorrelation of market-adjusted returns appears smallest for industry portfolios. That finding is somewhat misleading. Industry momentum persists for less than a year, but the estimates in Table 7 are based on the autocorrelation matrices for 18 months. The autocorrelations are stronger for the first 12 months, equal to 0.05 for the average industry.

Table 7
Serial correlation, market-adjusted returns, 1941–1999

Size portfolios

Past returns	$R_{\text{Small},t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{\text{Big},t}$
$R_{\text{Small},t-k}$	**0.10**	**0.09**	**0.09**	**0.05**	**-0.08**
$R_{2,t-k}$	**0.10**	**0.08**	**0.08**	**0.05**	**-0.08**
$R_{3,t-k}$	**0.09**	**0.08**	**0.08**	**0.05**	**-0.09**
$R_{4,t-k}$	**0.09**	**0.08**	**0.08**	**0.05**	**-0.08**
$R_{\text{Big},t-k}$	**-0.08**	**-0.08**	**-0.07**	-0.04	**0.08**
Mkt	**-0.09**	**-0.07**	**-0.07**	**-0.09**	**0.08**

B/M portfolios[a]

Past returns	$R_{\text{Low},t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{\text{High},t}$
$R_{\text{Low},t-k}$	0.03	**-0.09**	-0.02	-0.02	-0.03
$R_{2,t-k}$	-0.01	**0.05**	**0.06**	**0.06**	**0.05**
$R_{3,t-k}$	-0.02	**0.09**	**0.05**	**0.05**	**0.05**
$R_{4,t-k}$	**-0.10**	**0.12**	**0.09**	**0.10**	**0.10**
$R_{\text{High},t-k}$	**-0.10**	**0.10**	**0.07**	**0.08**	**0.08**
Mkt	-0.00	-0.04	0.02	-0.05	-0.07

Industry portfolios

Past returns	$R_{1,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{5,t}$	$R_{6,t}$	$R_{7,t}$	$R_{8,t}$	$R_{9,t}$	$R_{10,t}$	$R_{11,t}$	$R_{12,t}$	$R_{13,t}$	$R_{14,t}$	$R_{15,t}$
$R_{1,t-k}$	0.02	0.02	**0.06**	**0.05**	-0.01	0.03	-0.02	**-0.07**	-0.04	-0.01	**0.07**	-0.02	0.04	**0.09**	0.02
$R_{2,t-k}$	0.02	0.04	**0.05**	0.03	-0.01	-0.04	0.03	-0.03	**-0.07**	0.03	-0.01	0.03	-0.03	**0.07**	-0.01
$R_{3,t-k}$	-0.04	0.00	**0.10**	**0.05**	0.01	**0.07**	0.00	**-0.08**	**-0.05**	0.03	0.01	0.01	**0.07**	0.01	-0.04
$R_{4,t-k}$	0.03	-0.04	**0.07**	**0.08**	0.01	**-0.07**	0.02	0.01	**-0.05**	0.00	-0.02	0.03	0.03	**0.06**	0.04
$R_{5,t-k}$	**0.05**	**0.08**	0.01	-0.02	0.04	0.00	0.04	**-0.05**	**-0.12**	0.04	-0.01	-0.01	-0.02	0.02	**-0.08**
$R_{6,t-k}$	-0.01	0.02	-0.05	**-0.06**	-0.01	0.04	-0.04	-0.01	0.02	-0.02	-0.01	0.00	-0.03	**-0.06**	**-0.09**
$R_{7,t-k}$	0.00	0.02	0.01	-0.01	-0.04	0.02	0.00	**-0.05**	0.00	0.00	0.00	-0.01	0.01	0.04	-0.01
$R_{8,t-k}$	0.02	**-0.05**	-0.03	-0.01	0.00	**-0.08**	0.00	**0.06**	-0.01	-0.04	**0.07**	0.00	-0.01	0.04	**0.06**
$R_{9,t-k}$	0.00	0.03	0.00	0.00	0.02	-0.03	-0.01	**0.07**	0.00	-0.02	**-0.05**	0.02	-0.02	0.02	**0.08**
$R_{10,t-k}$	0.03	0.01	-0.02	-0.02	-0.01	-0.03	0.04	0.01	-0.02	0.01	-0.03	-0.04	**-0.09**	0.00	-0.02
$R_{11,t-k}$	0.01	-0.03	**0.05**	0.03	-0.01	0.00	0.01	0.03	0.02	0.00	0.03	-0.01	0.00	-0.02	**0.05**
$R_{12,t-k}$	-0.04	0.01	-0.01	**0.06**	0.03	0.00	-0.05	0.03	**0.05**	0.04	-0.04	0.00	0.04	**-0.10**	0.03
$R_{13,t-k}$	-0.01	-0.03	0.01	0.02	**0.05**	**0.07**	0.01	0.00	-0.03	0.02	0.01	-0.01	0.01	-0.03	-0.04
$R_{14,t-k}$	**-0.04**	-0.02	0.00	**-0.05**	**0.06**	**-0.05**	0.00	-0.02	-0.02	0.03	-0.02	0.03	0.04	-0.01	**-0.04**
$R_{15,t-k}$	0.01	-0.01	0.01	0.03	**0.07**	-0.01	0.01	0.02	-0.02	-0.02	-0.04	0.00	0.02	**0.06**	**0.04**
Mkt	-0.01	-0.02	-0.01	-0.07	0.00	-0.01	0.03	0.01	-0.01	-0.04	**-0.07**	**0.05**	**-0.05**	-0.03	**-0.05**

The table reports autocorrelations and cross-serial correlations for market-adjusted returns on industry, size, and B/M portfolios. The industries appear in the same order as in Table 1. Market-adjusted returns equal $r_i - r_{\text{vw mkt}}$. The table shows the average correlation, for lags of 1–18 months, between a portfolio's monthly returns and the past 12-month returns on all portfolios. The last row of each panel shows the correlation between market-adjusted returns and the past return on the value-weighted index. Bold denotes estimates that are significant at the 5% level based on bootstrap simulations.

[a] Statistics for May 1963–December 1999.

Table 7 contains one other piece of information about the predictability of market-adjusted returns. In the final row of each panel, I report the correlation between portfolio-specific returns and the lagged 12-month return on the CRSP value-weighted index. Interestingly, the table shows that market returns have strong predictive power. Focusing on size portfolios, the correlation is significantly negative for size quintiles 1–4 and significantly positive for quintile 5. The estimates are also significant for high B/M stocks and 5 of the 15 industries. In other words, portfolio-specific returns are not only predictable using the portfolio's own past returns, but they are also strongly predictable using the *market* return. That result is consistent with excess covariance in returns. It is not predicted by portfolio-specific underreaction, and helps explain why that model does not describe the autocorrelation patterns in Table 4 (see the discussion in 3.1).

3.5 The three-factor model
Either of the excess-covariance models could generate the serial correlation patterns in returns. So far I have not tried to distinguish between them. I take a step in this direction now, focusing on the Fama and French (1993) three-factor model.[13]

Before discussing the results, it is useful to provide some perspective on the tests. This article has considered, throughout, size and B/M portfolios that look much like the factors. The returns on size and B/M quintiles typically have three-factor R^2s close to 95%. It should come as little surprise, then, that the factors themselves exhibit momentum, or that the factors explain much of the momentum in size and B/M portfolios. However, that finding does not answer the basic question: why does momentum—in either the factors or the portfolios—arise in the first place? If the three-factor model explains momentum, this supports the argument that macroeconomic factors are important. But I would argue anyway that the returns on size and B/M portfolios are best interpreted as macroeconomic. Thus while the tests are interesting, I have left them until the end because the autocorrelations are more informative about the source of momentum.

To test whether the three-factor model absorbs momentum, I focus directly on profits rather than the autocorrelation patterns in returns. Table 8 shows two sets for results. The first row shows momentum profits earned by the Fama and French factors. The strategy is similar to before, investing in the factors in proportion to their past 12-month returns. The remaining rows show risk-adjusted profits for industry, size, and B/M portfolios. The three-factor model is used to adjust returns in both the formation and holding periods; in other words, both the investment weights and the reported profits are based

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[13] I thank Ken French for providing the factors, which can be found on his website at web.mit.edu/kfrench/www.

Table 8
Momentum profits using the three-factor model, 1941–1999

Assets	Month after formation								
	1	3	5	7	9	11	13	15	17
FF factors									
Average return	**0.609**	**0.372**	**0.368**	**0.373**	0.264	0.085	−0.054	−0.009	0.177
t-statistic	3.68	2.22	2.21	2.37	1.61	0.54	−0.34	−0.06	1.14
15 industry portfolios—FF residuals									
Average return	**0.590**	**0.434**	**0.304**	**0.200**	0.119	−0.038	−0.079	**−0.203**	−0.144
t-statistic	5.81	4.16	2.94	1.99	1.19	−0.40	−0.83	−2.19	−1.59
5 size portfolios—FF residuals									
Average return	**0.114**	**0.102**	**0.090**	0.071	0.043	0.026	−0.008	0.010	0.002
t-statistic	2.58	2.23	1.99	1.60	1.03	0.62	−0.19	0.24	0.05
5 B/M portfolios—FF residuals[a]									
Average return	0.084	0.059	0.092	0.061	0.052	0.036	−0.074	−0.101	−0.101
t-statistic	1.01	0.72	1.17	0.77	0.65	0.46	−0.97	−1.28	−1.31
9 size-B/M portfolios—FF residuals[a]									
Average return	**0.142**	0.037	0.033	0.015	0.028	−0.016	−0.078	−0.015	0.030
t-statistic	2.19	0.60	0.56	0.25	0.47	−0.28	−1.40	−0.29	0.54
25 size-B/M portfolios—FF residuals[a]									
Average return	**0.146**	0.066	0.037	−0.003	−0.011	−0.075	**−0.140**	**−0.091**	−0.068
t-statistic	2.30	1.08	0.64	−0.04	−0.19	−1.39	−2.56	−1.79	−1.29

The table reports profits for momentum strategies based on past 12-month returns. The first row reports a strategy using the Fama and French (1993) factors. The remaining rows use the three-factor model to adjust returns during both the formation and postformation period. To isolate time-series patterns in the residuals, the intercepts in the preliminary three-factor regressions are permitted to be nonzero. The momentum strategy invests in assets in proportion to their abnormal returns, scaled so the weights on both sides of the trade sum to $1. Returns are measured in percent. Bold denotes average returns greater than 1.645 standard errors from zero.

[a] Statistics for May 1963–December 1999.

on three-factor residuals.[14] The residuals for each portfolio are estimated from a full-sample regression, allowing the intercept to be nonzero.

The factors exhibit fairly strong momentum, although not as significant or persistent as those from size and B/M portfolios (see Table 2). Momentum profits decline from 0.61% in month 1 to 0.26% in month 9 (*t*-statistics = 3.68 and 1.61, respectively). The cumulative profit over the first six months is 2.60% (*t*-statistic = 2.81). This is similar to the profit from value-weighted size and B/M quintiles, but smaller than that from double-sorted size-B/M portfolios (3.43% for nine size-B/M portfolios, with a *t*-statistic = 4.11).

The three-factor model largely explains momentum in size and B/M portfolios, but not in industries. Over the first 6 months, industry profits equal 2.46% after adjusting for three-factor risk, down slightly from 3.04% for raw returns (the *t*-statistic remains above 4). This result is similar to the characteristic-adjusted profits in Table 3 [see also Moskowitz and Grinblatt (1999)]. In contrast, momentum in size and B/M quintiles, as well as 9 or 25 double-sorted portfolios, greatly diminishes. Comparing raw and

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[14] Note that I do not simply regress momentum profits from the earlier tables on the three-factor model. That approach is inappropriate because momentum portfolios' factor loadings change over time. Instead, the portfolio weights are determined by three-factor residuals, and the profit equals the weighted-average residual during the holding period.

adjusted returns over the first 6 months, profits drop from 2.56% to 0.60% for size quintiles, from 2.45% to 0.47% for B/M quintiles, and from 3.23% to 0.40% for 25 size-B/M portfolios. Of these, only the estimate for size portfolios remains significant (t-statistic = 2.42). Overall, the three-factor model appears to explain most, if not all, of the momentum in size and B/M portfolios.

4. Conclusion

There is now considerable evidence of momentum in stock returns. With the exception of Moskowitz and Grinblatt (1999), the literature argues that firm-specific returns drive momentum. Further, theoretical models of momentum, such as Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Sub-rahmanyam (1998), and Hong and Stein (1999), predict that stock returns will be positively autocorrelated.

This article shows that size and B/M portfolios exhibit momentum as strong as that in individual stocks and industries. That finding suggests that momentum is a pervasive feature of returns. Moreover, it implies that momentum cannot be attributed simply to firm-specific returns. The size and B/M portfolios are quite well diversified, so their returns reflect systematic risks. Macroeconomic factors, not firm-specific returns, must be responsible for size and B/M momentum.

In principle, size and B/M momentum might be explained by investor underreaction. However, that explanation seems unlikely from both an empirical and theoretical standpoint. Empirically the returns on industry, size, and B/M portfolios are negatively autocorrelated and cross-serially correlated. This rules out a simple underreaction model. However, it is potentially consistent with portfolio-specific underreaction, along with macroeconomic reversals, but this story also has a hard time explaining the evidence: (1) large stocks are weakly negatively autocorrelated, yet they predict other portfolios quite strongly (the cross-serial correlations are stronger than the underreaction story predicts); (2) market returns predict portfolio-specific returns on many size, B/M, and industry portfolios (a feature not anticipated by the underreaction story); and (3) the Fama and French (1993) three-factor model largely absorbs the serial correlation patterns in size and B/M portfolios.

Theoretically the underreaction story is unappealing because it says that investors react differently to portfolio-specific and market-wide news. No behavioral model predicts that result; indeed, I am aware of no model that explicitly distinguishes between firm-specific and market-wide returns. Perhaps more critically, news about size and B/M portfolios cannot reasonably be described as idiosyncratic. Thus a story in which investors react differently to idiosyncratic and macroeconomic news is not sufficient. Instead, a model needs to explain why investors underreact to some types of macroeconomic news, but overreact to others.

As an alternative to underreaction, I have proposed two models of excess covariance among stocks. Excess covariance means, loosely, that stock returns covary more strongly than dividends. In the first model, investors mistakenly believe that news about one firm contains information about other stocks. In the second model, stock prices react to changes in the aggregate risk premium. Both models generate autocorrelation patterns that are consistent with the data. Further, momentum and negative serial correlation come from the same underlying phenomenon.

There remain many unanswered questions about momentum. The most glaring omission of this article is evidence for individual stocks. Size and B/M momentum appears to be statistically distinct from individual-stock momentum. It would be useful to know whether they are caused by the same economic phenomenon, and in particular whether the excess-covariance models apply to individual stocks. There is evidence that individual-stock momentum might be explained by underreaction. For example, Bernard and Thomas (1990) argue that investors underreact to earnings announcements, although cross-serial correlation might complicate those results. The bottom line may well be that there are several sources of momentum in returns.

To close, I note that the evidence in this article should be interesting beyond its implications for momentum. The autocorrelation matrices, especially the cross-serial correlations, provide strong evidence of reversals in annual returns; the statistical significance is much stronger than suggested by previous studies [e.g., Fama and French (1988), Richardson (1993)]. Also, momentum in size and B/M portfolios, as well as in the Fama and French (1993) factors, implies that size and B/M effects change considerably over time; there would appear to be times when large stocks are expected to outperform small stocks, and when low B/M stocks are expected to outperform high B/M stocks. These observations could be important for investment decisions, testing asset pricing models, and evaluating the performance of mutual funds.

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