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Momentum, Business Cycle, and Time-varying Expected Returns

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ABSTRACT

A growing number of researchers argue that time-series patterns in returns are due to investor irrationality and thus can be translated into abnormal profits. Continuation of short-term returns or momentum is one such pattern that has defied any rational explanation and is at odds with market efficiency. This paper shows that profits to momentum strategies can be explained by a set of lagged macroeconomic variables and payoffs to momentum strategies disappear once stock returns are adjusted for their predictability based on these macroeconomic variables. Our results provide a possible role for time-varying expected returns as an explanation for momentum payoffs.

THIS PAPER EXAMINES THE RELATIVE importance of common factors and firm-specific information in explaining the profitability of momentum-based trading strategies, first documented by Jegadeesh and Titman (1993). The profitability of momentum strategies has been particularly intriguing, as it remains the only CAPM-related anomaly unexplained by the Fama–French three-factor model (Fama and French (1996)). Jegadeesh and Titman (2001) show that profits to momentum strategies continued in the 1990s, suggesting that their initial results were not due to data mining. Furthermore, the robustness of this strategy has been confirmed using data from stock markets other than the United States, where the profitability of this strategy was initially identified. Rouwenhorst (1998) finds momentum payoffs to be significantly positive in 12 other countries that were examined in his study. Also, Chan, Jegadeesh, and Lakonishok (1996) show that momentum strategies based on stock prices are distinct and separate from strategies based on earnings momentum. Even though investors underreact to earnings news, price momentum is not subsumed by momentum in earnings.

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Given that the strong robustness of momentum returns appears to be in conflict with the standard frictionless asset-pricing models, it is tempting to claim that market prices are driven by irrational agents. Jegadeesh and Titman (1993) have initially conjectured that individual stock momentum might be driven by investor underreaction to firm-specific information. More recently, Daniel, Hirshleifer, and Subrahmanyam (1998) and Barberis, Shleifer, and Vishny (1998) have attributed the momentum anomaly to investor cognitive biases.[1] Hong, Lim, and Stein (2000) report that holding size fixed, momentum strategies work better among stocks with low analyst coverage, consistent with the hypothesis that firm-specific information diffuses only gradually across the investing public. Lee and Swaminathan (2000) have shown that past trading volume predicts the magnitude and persistence of future price momentum, suggesting that trading volume is a proxy for investor interest in a stock and may be related to the speed with which information diffuses into prices.

The momentum anomaly is not without its share of efficient-markets-based explanations. Conrad and Kaul (1998) and Berk, Green, and Naik (1999) have argued that stocks with high (low) realized returns will be those that have high (low) expected returns, suggesting that the momentum strategy's profitability is a result of cross-sectional variability in expected returns. However, Grundy and Martin (2001) find that the expected returns measured from the Fama–French model or from a time-invariant expected return model fail to explain the profitability of momentum strategy. Jegadeesh and Titman (2001) argue that reversals in the post-holding period reject the claim of Conrad and Kaul that momentum profits are generated by dispersion in (unconditionally) expected returns. Furthermore, Jegadeesh and Titman argue that the results in Conrad and Kaul are driven by estimation errors in the estimation of expected return variance.

This paper analyzes the relative importance of common factors and firm-specific information as sources of momentum profit. We show that the profits to momentum strategies are explained by common macroeconomic variables that are related to the business cycle. Our analysis uncovers interesting time variation in payoffs from a momentum strategy. Returns to momentum strategies are positive only during expansionary periods. During recessions, the momentum strategy returns are negative, though statistically insignificant. Using a set of lagged macroeconomic variables to predict one-month-ahead returns, we show that the predicted part of returns is the primary cause of the observed momentum phenomenon. The variables we use in this prediction are standard macroeconomic variables known to predict market returns. These are dividend yield, default spread, yield on three-month T-bills, and term structure spread. We find that the momentum portfolios formed on the basis of past returns vary systematically in their sensitivity to these

[1] See Hirshleifer (2001) for a survey of the investor psychological biases that could impact asset prices.

macroeconomic variables. After controlling for the cross-sectional differences in predicted returns, the stock-specific returns contribute little to payoffs from momentum strategies.

In a recent paper, Moskowitz and Grinblatt (1999) conclude that the profitability of a momentum strategy is attributable primarily to momentum in industry factors. They argue that after controlling for momentum across industries, there is no momentum in individual stock returns except when a past 12-month return horizon is used to form the momentum portfolios. Given our findings that macroeconomic variables explain individual stock momentum payoffs, we investigate the link between industry returns and macroeconomic variables. Industry-based momentum returns are also captured by macroeconomic variables. Thus, both individual stock and industry momentum returns can be attributed to predictability in common factors rather than firm-specific or industry-specific returns. We show that the relationship between individual stock momentum and the macroeconomy is independent of the relationship between industry momentum and the macroeconomy. Finally, in our sample of NYSE–AMEX stocks, we find that the industry momentum is insufficient to fully explain the profitability of momentum strategies, even when return horizons shorter than 12 months are used to form momentum portfolios. This result is consistent with that of Grundy and Martin (2001), who show that individual stock- and industry-based momentum returns are distinct and separate phenomena.

One interpretation of our results is that the momentum payoffs are attributable to cross-sectional differences in *conditionally* expected returns that are predicted by standard macroeconomic variables. This interpretation is consistent with recent work that has pointed to the importance of the macroeconomy in determining cross-sectional variation in expected returns. For instance, studies by Bernanke and Gertler (1989), Gertler and Gilchrist (1994), and Kiyotaki and Moore (1997) predict that changing credit market conditions can have very different effects on small and large firms' risks and expected returns. Such theories also predict time variation in expected returns that is dependent on the state of the economy. In a related vein, Berk et al. (1999) present a theoretical model in which the value of a firm is the sum of the value of its existing assets and the value of growth options. In their model, the expected returns of stocks are determined jointly by the current interest rates, the average systematic risk of the firm's existing assets, and the number of active projects. Their model predicts that changes in interest rates will affect the expected stock returns differently for various firms, depending on the number of active projects. These theoretical arguments provide a direct link between cross-sectional dispersion of expected returns and the macroeconomic variables, particularly interest rates. Consistent with these theories, Perez-Quiros and Timmermann (2000) document larger variation in risk characteristics across business cycles for small firms than for large firms.

Further, consistent with the above interpretation of time-varying expected returns as the primary cause for stock momentum, we find that momentum profits obtain in different measurement periods around the formation period.

Specifically, with a formation period of 6 months, we find that momentum payoffs obtain not only in the following 6- and 12-month measurement periods but also in the 6 and 12 months prior to the formation period. To the extent that expected returns do not vary dramatically in the two-year period around the formation period, these results suggest that momentum profits could be driven by differences in conditionally expected returns across stocks.

We do not impose cross-sectional asset pricing constraints in this study. Proponents of the behavioral theories may well argue that, to be rational, the payoff to momentum strategies must covary with risk factors. Our goal in this paper is not to analyze the cross-sectional variation in mean returns, but rather to analyze the relative importance of common versus firm-specific sources of momentum payoffs. This is important because a common structure to the momentum profits points towards a rational risk-based explanation, whereas firm-specific sources of momentum payoffs are more consistent with the behavioral arguments. The main result of this paper, that momentum payoffs are captured by a parsimonious set of standard macroeconomic variables, raises the bar for the behavioral explanations of momentum. Behavioral explanations now have to incorporate this underlying structure in momentum payoffs.

The rest of the paper is organized as follows. The next section motivates the analysis. Section II presents the results, while Section III discusses alternative explanations for the results. Finally, Section IV presents our conclusions.

I. Empirical Specification

To study the relative importance of common factors and firm-specific information, we predict stock returns using standard macroeconomic variables and then examine whether momentum is attributable to the predicted component or the firm-specific component of returns. More specifically, we predict individual stock returns using the macroeconomic variables that prior studies have shown to predict market returns. These variables are the lagged values of the value-weighted market dividend yield, default spread, term spread, and yield on three-month T-bills.[2] The motivation for each of these variables is as follows.

We include the yield on the three-month T-bill since Fama (1981) and Fama and Schwert (1977) show that this variable is negatively related to future stock market returns and that it serves as a proxy for expectations of future economic activity. The dividend yield (*DIV*) on the market, defined as the total dividend payments accruing to the CRSP value-weighted index over the previous 12 months divided by the current level of the index, has been shown to be associated with slow mean reversion in stock returns across several economic cycles (Keim and Stambaugh (1986), Campbell and Shiller

[2] These variables have been used by Fama and French (1989) and Pontiff and Schall (1998). We thank Jeff Pontiff for providing us with the data.

(1988), Fama and French (1988)). This regressor is included as a proxy for time variation in the unobservable risk premium, since a high dividend yield indicates that dividends are being discounted at a higher rate. The default spread (*DEF*) is defined as the difference between the average yield of bonds rated BAA by Moodys and the average yield of bonds with a Moodys rating of AAA, and is included to capture the effect of default premiums. Fama and French (1988) show that default premiums track long-term business cycle conditions and document the fact that this variable is higher during recessions and lower during expansions. Finally, the term spread (*TERM*) is measured as the difference between the average yield of Treasury bonds with more than 10 years to maturity and the average yield of T-bills that mature in three months. Fama and French show that this variable is closely related to short-term business cycles.[3]

The predicted return is the one-period-ahead forecast from the following regression:[4]

$$R_{it} = c_{i0} + c_{i1}DIV_{t-1} + c_{i2}YLD_{t-1} + c_{i3}TERM_{t-1} + c_{i4}DEF_{t-1} + e_{it}. \qquad (1)$$

The parameters of the model, c_{ij}, are estimated each month, for each stock, using the previous 60 months of returns. To obtain meaningful parameter estimates, we restrict this regression to stocks that have at least 24 observations in the estimation period. The parameters of the model are then used to obtain the one-month-ahead predicted return for each stock.[5] Appendix A derives equation (1) in the context of a multi-beta framework with linear time-varying risk premia.

We do not impose equilibrium cross-sectional constraints related to asset pricing models as we do not test whether the payoff from the momentum strategy is related to its covariation with risk factors.[6] Nonetheless, equation (1) will allow us to test whether momentum payoffs are captured by a common set of standard macroeconomic variables. Proponents of the behavioral literature may well argue that, to be rational, momentum profits must covary with a pricing kernel and that our variables just happen to capture the autocorrelation structure of returns such that there is no remaining reward to momentum trading. However, it is still interesting to examine whether

[3] In addition to these variables, we used lagged values of the Fama–French factors as well as the book-to-market ratio for the value-weighted market index. The inclusion of these variables to predict returns does not alter our conclusions.

[4] In our analysis, we sometimes include a January dummy in the regression as well.

[5] To test the sensitivity of our results to inclusion of data from the portfolio formation period in estimating model parameters, we repeated the analyses after allowing for a six-month gap between the estimation period and the month for which returns are predicted (i.e., using data from the period $t - 67$ through $t - 7$ in each regression). This modification does not affect our conclusions.

[6] Note that the literature is still unsettled on the appropriate risk factors. See Fama and French (1992, 1993, 1996), Daniel and Titman (1997) and Daniel, Hirshleifer and Subrahmanyam (2001).

time-series variability in a few macroeconomic variables explains the payoffs to momentum trading, as this would raise the bar for irrational, underreaction explanations of momentum.

II. Empirical Results

A. Price Momentum

Table I replicates the momentum results of Jegadeesh and Titman (1993). For each month t, all NYSE–AMEX stocks on the monthly CRSP files with returns for months $t-6$ through $t-1$ are ranked into deciles based on their formation period ($t-6$ through $t-1$) returns. Decile portfolios are formed by weighting equally all firms in the decile rankings. The momentum strategy designates winners and losers as the top (P10) and the bottom (P1) portfolios and takes a long position in portfolio P10 and a short position in portfolio P1. The positions are held for the following six-month period, t through $t+5$, which is designated as the holding period. We follow Jegadeesh and Titman in forming decile portfolios that avoid test statistics based on overlapping returns. Note that with a six-month holding period, each month's return is a combination of the past six ranking strategies, and the weights of one-sixth of the securities change each month with the rest being carried over from the previous month.[7]

Table I documents the average monthly holding period returns over different time periods. The overall average momentum payoff for the period 7/26–12/94 is an insignificant +0.27 percent. However, this average is brought down by the pre-1951 period, during which the momentum payoff is an insignificant −0.61 percent. In the post-1951 period, the payoffs to a momentum strategy are significantly positive, earning 0.83 percent for the period 1/51–6/63 and 0.73 percent for the period 7/63–12/94.[8] Also, in the post-1951 period, the momentum payoffs are positive only during non-January months, while they are significantly negative in January. Grinblatt and Moskowitz (1999) argue that the negative returns in January are attributable to tax-loss selling of losing stocks at calendar year-end, which subsequently rebounds in January when the selling pressure is alleviated. Overall, while the results in the sample period after the 1950s confirm the momentum strategy profits documented in Jegadeesh and Titman (1993), the payoffs are insignificantly different from zero during the period 7/26–12/50.[9]

[7] We follow this technique in the rest of the paper.

[8] In all our analyses, results for the pre-1951 period are significantly different from those for post-1951 periods. However, the results are not statistically distinguishable across 1/51–6/63 and 7/63–12/94 subperiods. We footnote any deviations from this at relevant places.

[9] We have repeated the analysis of Table I after allowing for a one-month gap between the formation period ($t-7$ through $t-2$) and the holding period (t through $t+5$). A month's gap allows for an implementable strategy. Also, any bid-ask bounce effects are mitigated. The results from this analysis are, if anything, more significant than those of Table I. The payoff to a momentum strategy during 7/63–12/94 is a significant 1.02 percent per month.

Table I

Raw Momentum Strategy Payoffs

For each month t, all NYSE–AMEX stocks on the monthly CRSP tape with returns for months $t-6$ through $t-1$ are ranked into decile portfolios according to their return during that period. Decile portfolios are formed monthly by weighting equally all firms in that decile ranking. The momentum strategy designates winners and losers as the top (P10) and bottom (P1) portfolios and takes a long position in portfolio P10 and a short position in portfolio P1. The positions are held for the following six-month period (t through $t+5$), and this table shows the strategy's raw monthly profits, with t-statistics in parenthesis, during the holding period. The column titled "$\% > 0$" gives the percentage of P10 − P1 that are positive, and p-values from sign tests measuring deviations from 50 percent are given in parentheses below the percentage positive.

	Non-Jan				Jan				Overall			
Period	P1	P10	P10 − P1	$\% > 0$	P1	P10	P10 − P1	$\% > 0$	P1	P10	P10 − P1	$\% > 0$
7/26–12/94	0.40	1.33	0.92	67.24	11.70	4.68	−7.02	19.12	1.34	1.61	0.27	63.26
	(1.04)	(4.83)	(3.98)	(0.00)	(7.38)	(5.16)	(−6.54)	(0.00)	(3.39)	(6.06)	(1.10)	(0.00)
7/26–12/50	1.30	1.31	0.01	60.37	12.71	5.12	−7.59	16.67	2.23	1.62	−0.61	56.80
	(1.38)	(2.18)	(0.01)	(0.00)	(4.65)	(2.79)	(−4.34)	(0.00)	(2.45)	(2.82)	(−1.12)	(0.02)
1/51–6/63	0.23	1.48	1.25	70.07	5.67	1.98	−3.69	15.38	0.70	1.53	0.83	65.33
	(0.58)	(4.11)	(5.75)	(0.00)	(3.08)	(1.66)	(−2.97)	(0.02)	(1.69)	(4.43)	(3.28)	(0.00)
7/63–12/94	−0.22	1.28	1.51	71.47	13.45	5.48	−7.97	22.58	0.90	1.63	0.73	67.46
	(−0.58)	(3.72)	(6.52)	(0.00)	(5.20)	(4.24)	(−4.34)	(0.00)	(1.97)	(4.80)	(2.51)	(0.00)

Table II

Momentum Payoffs Classified by Business Cycles

Momentum payoffs are calculated by forming the winner (P10) and loser (P1) decile portfolios as described in Table I. This table presents the momentum payoffs (P10 − P1) in the holding periods that are classified into the various expansionary and contractionary periods as determined by the NBER (www.nber.org/cycles.html). *t*-statistics are reported in parenthesis.

Expansionary Periods		Contractionary Periods	
07/26–10/26	1.89	11/26–11/27	0.81
	(1.09)		(0.59)
12/27–08/29	2.12	09/29–03/33	−2.52
	(3.09)		(−1.10)
04/33–05/37	−1.94	06/37–06/38	−1.60
	(−1.38)		(−0.48)
07/38–02/45	−0.94	03/45–10/45	−1.03
	(−0.85)		(−1.39)
11/45–11/48	1.42	12/48–10/49	0.24
	(2.46)		(0.21)
11/49–07/53	0.60	08/53–05/54	1.43
	(1.64)		(0.96)
06/54–08/57	0.90	09/57–04/58	0.80
	(2.78)		(0.35)
05/58–04/60	0.85	05/60–02/61	1.03
	(1.57)		(0.91)
03/61–12/69	1.10	01/70–11/70	−0.42
	(2.67)		(−0.16)
12/70–11/73	1.33	12/73–03/75	−2.34
	(1.51)		(−0.74)
04/75–01/80	0.24	02/80–07/80	0.56
	(0.50)		(0.39)
08/80–07/81	0.89	08/81–11/82	2.60
	(0.80)		(2.79)
12/82–07/90	1.36	08/90–03/91	−4.22
	(3.36)		(−0.76)
4/91–12/94	0.34		
	(0.37)		
Mean	0.53	Mean	−0.72
	(2.35)		(−0.92)

B. Momentum and the Business Cycle

In this section, we analyze whether the profitability of momentum strategies is related to business cycles. We divide our sample into two economic environments—expansionary and recessionary periods, based on the NBER definition—and examine the payoffs to momentum strategies in each of these environments.[10]

Table II presents the payoffs to momentum strategies during the different business cycle periods. The results suggest that the momentum strategy payoffs are positive only during the expansionary periods when the marginal

[10] See www.nber.org/cycles.html.

utility of returns is likely to be lower. Each of the 10 postwar expansionary periods exhibited positive momentum payoffs, and four of these payoffs are statistically significant. On the other hand, six of nine postwar recessionary periods had positive momentum payoffs, and only one of these was statistically significant. Note that recessionary periods have shorter durations than expansionary periods. This may be the reason behind the lack of significance of momentum profits during recessions. However, this is unlikely to be a complete explanation, since three of nine postwar recessionary periods have negative momentum payoffs. Overall, momentum payoffs are negative during recessions and positive during expansions, and the difference in payoffs between the two periods is a statistically and economically significant 1.25 percent (t-statistic = 2.10) per month. This suggests that the source of profitability associated with momentum payoffs is related to the business cycle.

C. Predicted Returns Across Momentum Portfolios

We now explore the relative importance of the predicted and the unexplained components of returns in explaining momentum. We examine whether predicted returns in the holding period are different across momentum portfolios and whether these differences explain momentum payoffs. For this analysis, we restrict the sample for estimating equation (1) to begin from January 1951, so as to conform to the period after the Treasury–Federal Reserve Accord of 1951, which allowed T-bill rates to vary freely.

Figure 1 plots the predicted returns for momentum portfolios P1, P5, and P10. The decile portfolios are formed as before, by sorting raw returns in the formation period ($t - 6$ through $t - 1$). For Figure 1, parameter estimates for the business cycle model (1) are obtained using data from months $t - 7$ through $t - 67$. These parameter estimates are then used to calculate the predicted returns in each of the months $t - 12$ through month $t + 5$.[11] We repeat this analysis for each stock in each month. Thus, for each stock we have 18 event months: $t - 12$ through $t + 5$. All stock months are then aligned in the event month, classified by the momentum portfolio to which it belongs. Figure 1 presents the median predicted return over the event months for portfolios P1, P5, and P10.

The median predicted return for portfolio P10 is higher than that for portfolio P5, which in turn is higher than that for portfolio P1, in the formation period as well as in the six months before and after the formation period. The nonparametric sign test reveals that the difference in predicted returns between portfolios P10 and P1 is significant at the one percent level. This indicates that the component of returns related to macroeconomic variables varies systematically across momentum portfolios, suggesting that differences in predicted returns across momentum portfolios may account for the strategy's profitability.

[11] We have also calculated the parameters of model (1) each month (instead of keeping the parameters fixed over the formation and the holding periods) using the past five years of data. The qualitative results are essentially the same as those reported.

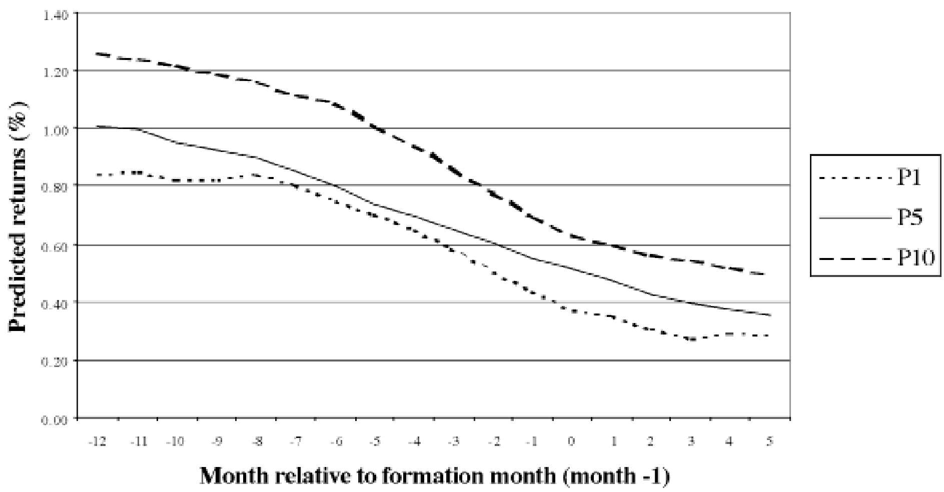

Figure 1. Median predicted returns around the formation period. For each month t, all NYSE–AMEX stocks on the monthly CRSP tape with returns for months $t - 6$ through $t - 1$ are ranked into decile portfolios according to their return during the period $t - 6$ through $t - 1$. Predicted returns are obtained from the following model: $R_t = \alpha + \beta \boldsymbol{X}_{t-1} + e_t$, where $\boldsymbol{X}$ is a vector representing the macroeconomic variables dividend yield (*DIV*), default spread (*DEF*), term spread (*TERM*), and the yield on the three-month T-bill (*YLD*). The model parameters are estimated using data from month $t - 7$ through month $t - 67$ and held constant over months $t - 12$ through $t + 5$. A minimum of two years of data is required. This figure shows the median predicted returns for the decile portfolios P1, P5, and P10 for the six months before the formation period, the six months during the formation period, and the six months following the formation period, that is, during the period $t - 12$ through $t + 5$. For all months, the median predicted return for P10 is higher than that of P5, which in turn is higher than that of P1.

D. Momentum Payoffs After Adjusting for Predicted Returns

Given the differences in predicted returns across momentum portfolios, we examine whether the momentum payoffs of Table I are fully explained by the predicted component of returns generated using model (1). If momentum payoffs are entirely explained by predicted returns, then the holding period returns from a momentum strategy should be insignificantly different from zero once the predictable component of returns is accounted for. For this analysis, we form momentum portfolios as before, that is, using raw returns. However, the holding period returns are now adjusted for the predicted return obtained from model (1) and represent the unexplained portion of returns defined as the intercept plus the residual. The intercept is excluded from the predicted portion of the model since the estimated intercept may capture some of the returns during the formation period and, as a result, could lead us to control for cross-sectional differences in average returns that are unrelated to the business cycle. In any case, it is worth noting that our results are essentially unchanged if the intercept is included in the predicted component of returns.

Table III

Momentum Strategy Payoffs Adjusted for Macroeconomic Variables

Winner (P10) and loser (P1) portfolios are formed in the manner described in Table I. Panels A and B show the strategy's holding period monthly profits after adjusting for returns predicted by the business cycle model. Adjusted returns are measured as the unexplained portion (intercept plus residual) of the following model: $R_t = \alpha + \beta \boldsymbol{X}_{t-1} + \theta JANDUM_t + e_t$, where $\boldsymbol{X}$ is a vector representing the predictor variables dividend yield, default spread, term spread, and the yield on the three-month T-bill. *JANDUM* (included only in Panel B) is a dummy variable that takes the value 1 for January and 0 in all other months. The model parameters are estimated using data from time $t - 1$ through $t - 60$. A minimum of two years of data is required for estimating the parameters. Panel C of this table presents the raw payoffs from the momentum strategy for the subsample of stock-months used in Panels A and B. t-statistics are reported in parenthesis. The column titled "% > 0" gives the percentage of P10 − P1 that are positive, and p-values from the sign test measuring deviations from 50 percent are given in parentheses below the percentage positive.

	Non-Jan		Jan		Overall	
	P10 − P1	% > 0	P10 − P1	% > 0	P10 − P1	% > 0
Panel A: Adjusted Payoffs—Business Cycle Model Excludes January Dummy						
1/53–12/94	−0.67	45.67	−16.30	31.71	−1.94	44.53
	(−0.47)	(0.07)	(−3.46)	(0.03)	(−1.41)	(0.02)
1/53–6/63	−2.65	43.48	−15.76	30.00	−3.70	42.40
	(−1.13)	(0.19)	(−1.80)	(0.34)	(−1.62)	(0.11)
7/63–12/94	−0.01	46.40	−16.47	32.26	−1.36	45.24
	(−0.01)	(0.20)	(−2.92)	(0.07)	(−0.81)	(0.07)
Panel B: Adjusted Payoffs—Business Cycle Model Includes January Dummy						
1/53–12/94	−1.01	45.89	−13.31	36.59	−2.02	45.13
	(−0.71)	(0.09)	(−2.95)	(0.12)	(−1.47)	(0.03)
1/53–6/63	−1.76	42.61	−12.61	40.00	−2.62	42.40
	(−0.79)	(0.14)	(−1.56)	(0.75)	(−1.23)	(0.11)
7/63–12/94	−0.77	46.97	−13.53	35.48	−1.81	46.03
	(−0.44)	(0.28)	(−2.49)	(0.15)	(−1.08)	(0.14)
Panel C: Raw Payoffs						
1/53–12/94	1.39	70.35	−7.27	21.95	0.69	66.40
	(7.60)	(0.00)	(−4.83)	(0.00)	(2.95)	(0.00)
1/53–6/63	1.39	73.04	−4.83	10.00	0.90	68.00
	(5.86)	(0.00)	(−3.36)	(0.02)	(3.11)	(0.00)
7/63–12/94	1.39	69.45	−8.06	25.81	0.62	65.87
	(6.03)	(0.00)	(−4.18)	(0.01)	(2.10)	(0.00)

Panels A and B of Table III present the average payoffs to a momentum strategy after controlling for the predicted returns in the holding period. In contrast to Figure 1, the predicted returns for this table and the remainder of the tables are the one-month-ahead forecasts from a set of rolling regressions. Focusing on the business cycle model that does not include the January dummy in Panel A, we find that during 7/63–12/94, the average monthly momentum payoff after controlling for predicted returns is an insignificant −1.36 percent, while during 1/53–6/63 it is an insignificant −3.70 percent. During 1/53–12/94, the momentum payoff is negative but statistically insignificant.[12] The results are similar when the return prediction model in equation (1) includes a January dummy in Panel B.[13] These results suggest that recent stock returns do not predict the portion of future returns that is unexplained by the business cycle model, and the predictive ability of past returns is restricted to the portion of returns that is predictable by macroeconomic variables. We test this more directly in Table VI.

E. Momentum Payoffs Regressed on Macroeconomic Variables

One concern with the above analysis is the explanatory power of our business-cycle model. The average adjusted R^2 when the January dummy is included (excluded) in the model is about 6 percent (3.5 percent). In comparison, Pontiff and Schall (1998) report an adjusted R^2 of 7 percent when the CRSP value-weighted market return is the dependent variable and 9 percent when the equally weighted market return is the dependent variable. Clearly, with individual stocks, the signal-to-noise ratio will be lower. Further, we use only the past 60 months of data for each regression, whereas the Pontiff and Schall regressions pertain to the entire sample period, 7/59–8/94. Jegadeesh and Titman (2001) have argued that estimation errors in calculating expected returns in Conrad and Kaul (1998) result in a downward bias in estimates of serial covariation of firm-specific returns. While our business-cycle model has low R^2s, our estimate of forecasted returns is likely to have lower estimation errors than the unconditional mean estimates of Conrad and Kaul.[14]

[12] Since we need at least two years of data to estimate equation (1), the samples for Table I and Table III are different. To check that the results from this analysis are not being driven by sample selection, we replicate the results of Table I for the subsample of stock-months in Panels A and B. Panel C of Table III shows that the mean payoffs for this subsample of stock-months are significantly positive in the post-1951 period. We have also repeated the analysis of Table III after allowing for a one-month gap between the formation period and the holding period, and the results remain essentially unchanged.

[13] To test whether the differences in predicted returns are as persistent as the momentum payoffs, we reexamined the momentum payoffs using a 12-month holding period. The results show that the raw profits from this strategy are a significant 0.69 percent per month (t-statistic = 3.66) for our sample period 1/53–12/94. Upon adjusting for predicted returns, estimated from the business cycle model, the momentum payoffs are insignificant and less than 0.1 percent per month in magnitude.

[14] To test whether the fit of the model drives our results, we divide our sample of winner and loser stocks into two momentum portfolios, one with high adjusted R^2 stocks and the second with low R^2 stocks. The low R^2 portfolio has momentum payoff point estimates that are less negative than those of the high R^2 portfolio (although both are statistically insignificant), suggesting that the model fit or the lack thereof does not drive our results. Also, the correlation between the adjusted R^2s and predicted returns is an insignificant +0.03, suggesting that the low explanatory power of our model does not bias upwards the estimate of predicted returns. A positive value for the correlation indicates that the predicted returns are, if anything, biased downwards and hence less likely to explain momentum.

To reduce noise in the parameter estimates that arises with the use of individual stock regressions in equation (1), we examine the link between momentum payoffs and macroeconomic variables directly by regressing the time series of raw momentum payoffs (P10–P1) on our macroeconomic predictor variables. To allow for a time-varying relationship between macroeconomic variables and momentum payoffs, we regress the momentum payoffs on the predictor variables using the past five years of data and use the estimated parameters to predict the one-month-ahead payoffs.[15] The unexplained return (*RES*) for each month is then calculated as the estimated intercept plus the prediction error. We require at least one year of data for these regressions, and since the rolling regressions introduce autocorrelation in estimates, the t-statistics are based on the Newey–West (1987) autocorrelation consistent standard errors. If the business-cycle model (1) fails to fully explain momentum payoffs, we expect the unexplained portion (*RES*) of the regression to be significantly positive.

Panel A of Table IV presents the time-series averages of the intercept (*INT*), the payoff that is unexplained by lagged macroeconomic predictor variables (*RES*), and the time-series averages of the coefficients on predictor variables. Both *INT* and *RES* are negative during the period 1/52–12/94. The coefficients on default spreads are significantly negative during 7/63–12/94, whereas the coefficients on term spreads and on three-month T-bill yields are significantly positive during both the subperiods 1/52–6/63 and 7/63–12/94. The negative coefficient on default spread suggests that controlling for this variable should actually increase the profitability of momentum strategies. However, the effect of this variable is more than offset by the relationship between momentum payoffs and term spreads and the yield on the three-month T-bill. The differences in the coefficients suggest systematic differences across the winner and loser portfolios in their exposures to the business cycle.

Panel B replicates the results when a January dummy is used in the return prediction model (1). The *INT* and *RES*, while negative, are not always significant once adjustment is made for the significantly negative January returns. Nonetheless, the negative values for *INT* and *RES* are consistent with the findings of Conrad and Kaul (1998), who report that the cross-sectional variation in mean returns typically explains more than 100 percent of the momentum profits, and that after controlling for the mean returns, negative profits are obtained from momentum strategies.[16]

[15] The results from using data in the 12 months prior to each month t, rather than the prior 60 months, are quite similar, although the parameter estimates tend to be noisy with a shorter estimation period.

[16] To test the robustness of the above results to the period used to estimate model parameters, we have repeated the above tests using forward-looking data in the regression of momentum payoffs on the macroeconomic variables. For each month t, the model parameters were estimated using the data in the period $t + 1$ through $t + 61$, and these parameter estimates were then used to predict the payoffs for month t. The results (available upon request) confirm our above findings and show that after controlling for returns predicted by model (1), the momentum strategy is no longer profitable.

Table IV

Momentum Payoffs Regressed on Macroeconomic Predictor Variables

Winner (P10) and loser (P1) portfolios are formed in the manner described in Table I. This table presents the average coefficients when momentum strategy payoffs (P10 − P1) are regressed against lagged values of the macroeconomic predictor variables dividend yield, default spread, term spread, and the yield on the three-month T-bill. *JANDUM* (included only in Panel B) is a dummy variable that takes the value 1 for January and 0 in all other months. *RES* represents the average unexplained returns. For each month t, the returns unexplained by the returns model are computed as intercept (*INT*) plus month t's residual. For each month t, the parameters are estimated by using payoffs in months $t - 60$ through $t - 1$. A minimum of one year of data is required for the estimation period. t-statistics (in parentheses) are based on Newey–West autocorrelation consistent standard errors. The column titled "% *RES* > 0" gives the percentage of P10 − P1 that are positive, and p-values from the sign test measuring deviations from 50 percent are given in parentheses below the percentage positive.

Panel A: Regression Excludes January Dummy

Period	*RES*	% *RES* > 0	*INT*	*DIV*	*DEF*	*TERM*	*YLD*
1/52–12/94	−9.67	21.12	−9.09	0.08	−4.43	3.56	2.62
	(−3.71)	(0.00)	(−3.42)	(0.10)	(−1.65)	(5.37)	(4.92)
1/52–6/63	−18.92	2.19	−18.66	1.47	0.82	5.26	4.04
	(−5.85)	(0.00)	(−5.66)	(2.31)	(0.19)	(4.76)	(7.28)
7/63–12/94	−6.29	28.04	−5.60	−0.42	−6.35	2.94	2.10
	(−2.60)	(0.00)	(−2.31)	(−0.42)	(−2.06)	(3.93)	(3.43)

Panel B: Regression Includes January Dummy

Period	*RES*	% *RES* > 0	*INT*	*JANDUM*	*DIV*	*DEF*	*TERM*	*YLD*
1/52–12/94	−5.15	31.78	−4.77	−7.49	0.05	−2.03	2.15	1.74
	(−2.13)	(0.00)	(−1.92)	(−6.46)	(0.06)	(−0.92)	(3.78)	(3.95)
1/52–6/63	−14.04	10.87	−13.91	−4.31	0.84	3.76	3.45	3.05
	(−3.39)	(0.00)	(−3.31)	(−3.44)	(2.85)	(1.04)	(2.32)	(3.97)
7/63–12/94	−1.90	39.42	−1.44	−8.66	−0.24	−4.15	1.68	1.26
	(−1.00)	(0.00)	(−0.73)	(−6.77)	(−0.23)	(−1.79)	(3.22)	(3.02)

To ascertain that our earlier results are not unique to a specific subperiod, we regressed the monthly momentum payoffs in each five-year subperiod on the macroeconomic predictor variables. The choice of five-year subperiods was based on a compromise between having time-varying coefficients and having sufficient observations to get meaningful parameter estimates. Since, unlike our earlier analysis, these regressions are independent across subperiods, the results in Table V also provide a robustness test for whether our earlier results are influenced by insufficient correction for autocorrelation.

The results in Panel A of Table V indicate that the intercept from the regression is negative in six out of nine of the subperiods. Moreover, the coefficients on *TERM* and *YLD* are positive in all nine of the subperiods. The t-statistics for the average coefficients over the period 1951–1994 are calculated under the null of independent draws across the subperiods. The

Table V

Momentum Strategy Payoffs Regressed on Macroeconomic Predictor Variables: Five-year Subperiod Results

Winner (P10) and loser (P1) portfolios are formed in the manner described in Table I. This table presents coefficients and *t*-statistics obtained when momentum strategy payoffs (P10 − P1) are regressed against lagged values of the macroeconomic predictor variables dividend yield, default spread, term spread, and the yield on the three-month T-bill. *JANDUM* (included only in Panel B) is a dummy variable that takes the value 1 for January and 0 in all other months. The regressions are carried out separately for each five-year subperiod.

Panel A: Business Cycle Model Excludes January Dummy

	INT		*DIV*		*DEF*		*TERM*		*YLD*		
Subperiod	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Adj R^2
1951–1955	−16.28	−1.89	0.21	0.39	8.29	1.27	5.00	1.62	3.75	1.67	0.02
1956–1960	−24.91	−2.07	4.42	2.17	−12.66	−2.88	6.00	2.44	5.00	2.56	0.10
1961–1965	−18.55	−0.53	−3.03	−1.17	17.10	1.21	1.68	0.23	5.80	0.73	−0.02
1966–1970	5.55	0.72	−4.74	−1.91	−5.74	−1.01	5.32	2.03	2.70	1.79	0.04
1971–1975	−18.91	−1.20	−4.22	−1.60	−6.92	−1.55	7.99	1.87	6.47	1.86	0.09
1976–1980	−11.81	−1.71	1.30	0.87	−1.47	−0.74	1.59	1.48	1.00	1.48	0.04
1981–1985	−9.33	−1.16	0.92	0.41	0.80	0.32	1.05	0.81	0.40	0.38	0.02
1986–1990	1.15	0.09	0.47	0.22	−3.61	−0.73	0.03	0.02	0.43	0.30	−0.01
1991–1994	17.48	0.78	−9.89	−0.92	−26.81	−3.05	3.17	1.12	4.95	1.51	0.22
Average	−8.40	−1.83	−1.62	−1.14	−3.45	−0.83	3.54	3.97	3.39	4.32	0.06

Panel B: Business Cycle Model Includes January Dummy

	INT		*DIV*		*DEF*		*TERM*		*YLD*		*JANDUM*		
Subperiod	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Adj R^2
1951–1955	−14.32	−1.69	0.12	0.23	9.94	1.54	3.87	1.26	3.17	1.42	−2.27	−1.90	0.06
1956–1960	−11.37	−1.11	2.20	1.28	−7.15	−1.90	2.56	1.21	2.87	1.74	−6.65	−5.25	0.39
1961–1965	−21.98	−0.76	−2.61	−1.20	16.64	1.41	2.75	0.44	6.44	0.97	−6.21	−4.95	0.28
1966–1970	8.26	1.13	−5.36	−2.28	−5.69	−1.06	4.77	1.93	2.66	1.87	−7.39	−2.81	0.15
1971–1975	8.65	0.70	−2.16	−1.09	−2.96	−0.88	0.31	0.09	0.57	0.21	−18.71	−6.82	0.50
1976–1980	−11.15	−1.61	1.39	0.92	−1.20	−0.60	1.36	1.23	0.86	1.23	−1.74	−0.99	0.03
1981–1985	−6.47	−0.93	0.94	0.49	1.04	0.48	0.72	0.64	0.17	0.19	−6.98	−4.50	0.28
1986–1990	−10.87	−0.99	1.61	0.93	1.38	0.33	0.05	0.05	0.98	0.84	−8.83	−5.29	0.32
1991–1994	24.66	1.22	−11.34	−1.17	−18.62	−2.25	1.81	0.70	3.94	1.33	−12.07	−3.34	0.37
Average	−3.84	−0.79	−1.69	−1.16	−0.74	−0.22	2.02	3.76	2.41	3.59	−7.87	−4.61	0.26

average coefficients suggest that the intercept is negative and the coefficients of *TERM* and *YLD* are significantly positive. Panel B of Table V replicates the analysis when the January dummy is included as an independent variable in the regression. Now the coefficient on the January dummy is significantly negative, and the intercept is no longer significantly different from zero. Also, the adjusted R^2 are much higher in the presence of the January dummy. Overall, the results are consistent with those of Table IV, and show that the earlier results are not driven by any particular subperiod.

The results in Tables III through V show that we cannot reject the null hypothesis of zero momentum payoffs once holding period returns are adjusted for their predictability using standard macroeconomic variables, particularly *TERM* and *YLD*. These results also suggest that predicted returns are at least as persistent as the momentum payoffs. However, it is possible that the momentum payoffs are actually driven by past raw returns and that our business cycle model simply captures the information contained in the past returns. The following two sections address this concern.[17]

F. Role of Predicted and Stock-specific Returns in Causing Momentum

In this section, we address the concern that our earlier results are due to the possibility that the model is simply capturing information contained in past raw returns. We do this by investigating whether momentum payoffs are attributable to the predicted portion of the business-cycle model or the unexplained portion of the returns. If the predicted returns are persistent and if momentum is attributable only to the predicted part of returns, then only momentum strategies based on predicted returns (and not on stock-specific returns or unexplained portion of returns) should yield positive payoffs.

To compare the profitability of momentum strategies based on components of returns predicted by macroeconomic variables with the profitability from strategies that are based on the unexplained component of returns (or stock-specific returns), we follow the approach of Grundy and Martin (2001). For each stock i and for each month t, stock-specific returns are compounded in the prior six months, and these compound returns are then used to form the decile portfolios. Each month, the predicted and stock-specific returns are formed as follows. Using equation (1) to forecast the one-period-ahead return for each stock gives the predicted return. As before, the unexplained (or stock-specific) return is defined as the intercept from the business-cycle model (1) plus residual or forecast error.[18] The momentum strategy based on these stock-specific returns then buys the stocks with the greatest stock-specific returns during the formation period and short-sells stocks with the least stock-specific returns. The positions

[17] To conserve space, the rest of the paper focuses only on results from the return prediction model that excludes the January dummy. However, the results (available upon request) are qualitatively unaffected when the January dummy is included in the model.

[18] Our results do not change whether or not we include the intercept from equation (1) in the definition of unexplained returns.

Table VI

Payoffs from a Momentum Strategy Based on Business-cycle-adjusted (or Predicted) Returns

For each month t, all NYSE–AMEX stocks i on the monthly CRSP tape are ranked into decile portfolios according to their business-cycle-adjusted returns (Panel A) or predicted returns from the business cycle model (Panel B) during the period $t - 6$ through $t - 1$. For each firm i and for each month t, the business-cycle-adjusted returns and predicted returns are computed by estimating the following model: $R_t = \alpha + \beta \boldsymbol{X_{t-1}} + e_t$, where $\boldsymbol{X}$ is a vector representing the macroeconomic variables, dividend yield, default spread, term spread, and the yield on the three-month T-Bill. The adjusted returns are given by the unexplained portion of the model (intercept plus residual), while the predicted returns are given by the predicted portion of the model. The model parameters are estimated using data from time $t - 1$ through $t - 60$. A minimum of two years of data is required for estimating the parameters. Decile portfolios are formed monthly by weighting equally all firms in that decile ranking. The momentum strategy designates winners and losers as the bottom (P1) and top (P10) portfolios and takes a long position in portfolio P10 and a short position in portfolio P1. The positions are held for the following six-month period (t through $t + 5$), and this table shows the strategy's monthly profits (raw returns) during the holding period. t-statistics are reported in parenthesis. The column titled "% > 0" gives the percentage of P10 − P1 that are positive, and p-values from the sign test measuring deviations from 50 percent are given in parentheses below the percentage positive.

	Non-Jan		Jan		Overall	
	P10 − P1	% > 0	P10 − P1	% > 0	P10 − P1	% > 0
Panel A: Deciles Formed Based on Unexplained Returns						
1/53–12/94	−0.10	47.81	0.36	68.29	−0.06	49.50
	(−0.79)	(0.37)	(0.39)	(0.03)	(−0.44)	(0.86)
1/53–6/63	−0.59	38.53	2.28	90.00	−0.35	42.86
	(−3.11)	(0.02)	(4.01)	(0.02)	(−1.79)	(0.14)
7/63–12/94	0.06	50.72	−0.26	61.29	0.03	51.59
	(0.38)	(0.83)	(−0.22)	(0.28)	(0.18)	(0.57)
Panel B: Deciles Formed Based On Predicted Returns						
1/53–12/94	0.93	66.16	−4.56	29.27	0.48	63.15
	(6.42)	(0.00)	(−3.73)	(0.01)	(2.70)	(0.00)
1/53–6/63	0.88	70.18	−3.97	20.00	0.49	66.13
	(4.31)	(0.00)	(−3.01)	(0.11)	(2.01)	(0.00)
7/63–12/94	0.95	64.84	−4.76	32.26	0.48	62.17
	(5.24)	(0.00)	(−3.03)	(0.07)	(2.14)	(0.00)

are then held for the subsequent six-month period. Panel A of Table VI presents the raw profits from this strategy. The results indicate that payoffs from momentum strategies based on stock-specific returns are insignificantly different from zero. During 1/53–12/94 the momentum payoffs average an insignificant −0.06 percent per month, and only 49.5 percent of the payoffs are positive. These results are in contrast to the results reported in Grundy and Martin, where all the payoffs were attributed to the component of returns unexplained by the Fama–French three-factor model.

The above results, when viewed together with the results reported in Table I for momentum strategy based on raw returns, suggest that the profitability of the raw momentum strategies must arise from the predicted component of returns. We confirm this by directly examining the profitability of a momentum strategy that forms portfolios based on the predicted returns. This analysis also enables us to contrast the profitability of the momentum strategy based on stock-specific returns with that based on the predicted returns. The raw holding period returns for this strategy are reported in Panel B of Table VI. The payoffs from momentum strategies using the predicted returns are significantly positive. During 1/53–12/94, the momentum payoffs average a significant 0.48 percent per month, and 63 percent of them are positive. Further, these payoffs are significantly greater than those obtained from strategies based on unexplained returns, suggesting that it is the predicted returns and not the idiosyncratic component of returns that drive profits to the momentum strategy of buying winners and selling losers.

G. Predicted Versus Raw Returns

As an additional test for examining the importance of common macroeconomic variables in explaining stock momentum, we conduct a horse race between momentum portfolios based on past raw returns and on the component of past returns that are predicted by the macroeconomic variables. We compare payoffs from momentum strategies formed using only the predicted component of returns in the formation period with payoffs from trading strategies that use the raw returns in the formation period. If stock momentum is attributable to both firm-specific information and common factors, then we expect payoffs from stocks sorted on raw returns to yield momentum payoffs, even when there are no cross-sectional differences in predicted returns. However, if momentum is attributable only to common factors, we expect stocks sorted on predicted returns to yield significant payoffs even after controlling for cross-sectional differences in total returns.

We generate portfolios based on two-way sorts, using the predicted returns from equation (1), as well as past returns. At the beginning of each month, all stocks are first sorted into quintiles by their buy-and-hold raw returns over the prior six months (or their predicted returns). Stocks in each quintile are then assigned to one of five equal-sized portfolios based on their predicted returns (or their raw returns). The two-way sorts result in 25 portfolios. All stocks are equally weighted in a portfolio. The two-way sorts allow us to estimate the momentum payoffs based on sorting by raw returns while holding predicted returns constant and vice versa.[19]

[19] Instead of sorting sequentially, we have repeated the analysis in Table VII based on independent sorting of stocks based on raw returns and predicted returns and have reached similar conclusions.

For each portfolio, Table VII shows the average monthly return during the holding period, which is the six months subsequent to the portfolio formation date. In Panel A of Table VII, the portfolios are formed by sorting, first by raw returns and then by the predicted returns. The holding period returns, across the portfolios formed on the basis of raw returns, increase monotonically for all predicted return quintiles. However, the strategy that buys winners and sells losers based on raw returns is found to earn significantly positive payoffs only for the highest two predicted return quintiles. More interestingly, the returns across predicted return quintiles also increase monotonically even when their ranking based on raw returns is kept constant. For instance, the average monthly returns for firms in the highest raw return quintile vary from 1.28 percent to 1.74 percent based on their predicted returns. With the exception of the firms in the lowest raw return quintile, momentum strategies using predicted returns yield significantly positive payoffs within each raw-return quintile. This suggests that portfolios formed on the basis of predicted returns are able to earn significant profits even after controlling for momentum based on past returns.

However, the results are quite different when the portfolios are formed by first sorting based on predicted returns and then on raw returns. The results in Panel B show that the average returns increase monotonically across the predicted return quintiles within each raw-return quintile. However, within each of the predicted return quintiles, no pattern in the holding period returns is discernible across the raw-return quintiles. Also, the holding period returns are not significantly different between the low raw-return and the high raw-return quintiles. The only exception to these is the highest predicted return quintile, where the average momentum payoff based on raw returns is a statistically significant 0.40 percent per month. The results in this panel, when combined with those presented in Panel A, suggest that the momentum payoffs are being driven mainly by strategies based on past predicted returns, rather than on past returns. These results are particularly noteworthy given the low fit of the model (1) and the fact that our estimation procedure requires model parameters to be constant over five years, as compared with the strategy based on raw returns, which requires only six months of data.

The results in this section and the previous section suggest that the predicted returns from our model are not simply capturing the effect of past returns, but in fact, the reverse is true—the ability of past raw returns to predict future returns is due to information contained in the predicted component of returns.[20] Furthermore, these results provide support for our contention that the results in Table III are not driven by the low explanatory power of our return prediction model (1). Overall, the results in Tables VI

[20] The results in Table V can also be interpreted as further evidence that our results in Table III are not driven by the return prediction model (1) capturing information contained in past returns. This is because the results in Table V show that the momentum profits can be directly explained by macroeconomic variables, rather than the past six-month raw returns.

Table VII

Holding Period Returns for Portfolios Ranked by Raw Returns and Predicted Returns

In Panel A, at the beginning of each month, all stocks are first sorted into quintiles by their buy and hold raw returns over the prior six months. Stocks in each quintile are then assigned to one of five equal-sized portfolios based on their predicted returns from a business cycle model compounded over the prior six months. In Panel B, stocks are first sorted by predicted returns and then by raw returns. The predicted return is given by the fitted values from the following regression: $R_t = \alpha + \beta \boldsymbol{X_{t-1}} + e_t$, where $\boldsymbol{X}$ is a vector representing the macroeconomic variables dividend yield (*DIV*), default spread (*DEF*), term spread (*TERM*), and the yield on the three-month T-bill (*YLD*). This regression is run for each stock using returns in the prior 60 months. A minimum of 12 months of data is required. The two-way sorts result in 25 portfolios. All stocks are equally weighted in a portfolio. For each portfolio, the table shows the average monthly buy-and-hold return for the first six months in the postformation period. The sample period is July 1963 through December 1994. t-statistics are reported in parenthesis.

	Raw Returns						
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5) − (1)	t-stat ((5) − (1))
Panel A: Sorted First by Past Raw Returns and Then by Predicted Returns							
1 (low)	1.08	1.08	1.15	1.16	1.28	0.20	(0.61)
2	0.94	1.14	1.18	1.25	1.37	0.43	(1.66)
3	1.13	1.27	1.31	1.30	1.55	0.42	(1.87)
4	1.18	1.35	1.42	1.45	1.71	0.53	(2.31)
5 (high)	1.30	1.44	1.53	1.55	1.74	0.44	(1.97)
Difference (5) − (1)	0.22	0.36	0.39	0.40	0.46		
t-stat ((5) − (1))	(0.86)	(3.17)	(3.57)	(3.46)	(3.46)		
Panel B: Sorted First by Predicted Returns and Then by Past Raw Returns							
1 (low)	1.04	1.02	1.08	1.12	1.18	0.14	(0.45)
2	1.10	1.21	1.14	1.16	1.30	0.19	(1.06)
3	1.20	1.28	1.28	1.27	1.33	0.13	(0.71)
4	1.35	1.44	1.46	1.44	1.61	0.26	(1.44)
5 (high)	1.38	1.51	1.54	1.67	1.78	0.40	(1.99)
Difference (5) − (1)	0.34	0.49	0.46	0.55	0.60		
t-stat ((5) − (1))	(1.12)	(2.59)	(2.76)	(3.36)	(3.82)		

and VII strongly support the view that momentum payoffs are attributable primarily to a common set of factors, rather than to firm-specific returns. In particular, momentum payoffs are attributable primarily to predicted returns as obtained from a common set of macroeconomic variables, strongly suggesting that predicted returns are persistent and it is this persistence in predicted returns that gives rise to momentum. It may also be worth pointing out here that the persistence in predicted returns are consistent with gradual variation in expected returns relating to business cycle conditions, an issue we discuss further in Section III.

Thus far, we have formed portfolios based on past returns or based on predicted returns of individual stocks. We now turn to momentum in industry portfolios.

H. Momentum in Industry Portfolios

Moskowitz and Grinblatt (1999) document a strong momentum effect in industry components of stock returns and argue that the industry momentum fully explains payoffs from strategies based on past six-month returns. This section examines the relationship between the business cycle and momentum in industry returns and investigates whether it is the industry returns or the component of returns predicted by macroeconomic variables that better explains individual stock momentum.

To set the stage, we initially replicate the Moskowitz–Grinblatt industry momentum results for our sample of NYSE–AMEX stocks. For each month t, all NYSE–AMEX stocks on the monthly CRSP tapes are used to compute equally weighted industry returns. The 20 industry classifications used for this study are the same as those used in Moskowitz and Grinblatt (1999). The time series of industry returns is then used to form the winner (P10) and the loser (P1) portfolios. The winner (loser) portfolio is the equally weighted return of the two industries with the highest (lowest) raw returns in the formation period, $t - 6$ through $t - 1$. The momentum payoff (P10 − P1) is then computed over the holding period, t through $t + 5$. Panel A of Table VIII presents the results.

Consistent with Moskowitz and Grinblatt (1999), the payoffs to an industry momentum are significantly positive over the 7/26–12/94 period, with a monthly average of 0.58 percent. The payoffs are positive in approximately 66 percent of the months. Focusing on the subperiods, the payoffs to industry momentum are found to be significantly positive in the post-1951 period only. The average monthly payoff is over 0.8 percent in the post-1951 period, while it is an insignificant 0.06 percent during 7/26–12/50. Further, unlike the momentum payoffs of individual stock returns, the industry momentum payoffs in the post-1951 period are positive in both January and the non-January months.

Panel B of Table VIII presents the momentum payoffs to industry portfolios after the industry returns have been adjusted for their predictability based on macroeconomic variables. As before, momentum deciles are formed by classifying industries based on past six-month returns. However, now the holding period returns are adjusted for predicted returns, which are the one-period-ahead forecasts from the business cycle model in equation (1). The results show that the industry momentum strategy of buying winners and selling losers is not profitable once differences in predicted returns across industries are controlled for. In the period 1/53–12/94, the momentum payoff unexplained by macroeconomic variables is −1.97 percent per month. Moreover, the unexplained portion of momentum payoffs is negative during

Table VIII

Payoffs from Momentum Strategy Based on Industry Returns

For each month t, all NYSE–AMEX stocks on the monthly CRSP tape are used to compute the equally weighted industry returns. The 20 industries are classified as in Moskowitz and Grinblatt (1999). The time series of industry returns is then used to form the momentum portfolios by ranking industries according to their return during the period $t-6$ through $t-1$. Winner (P10) and loser (P1) industry portfolios are formed monthly by weighting equally the top two and the bottom two industry returns, respectively. The momentum strategy takes a long position in P10 and a short position in P1. The positions are held for the following six-month period (t through $t+5$). Panel A shows the strategy's raw monthly payoffs during the holding period, while Panel B shows the holding period payoffs after adjusting for predicted returns. Predicted returns are the one period ahead forecast returns (not including the intercept) from the following model: $R_t = \alpha + \beta \boldsymbol{X_{t-1}} + e_t$, where $\boldsymbol{X_t}$ is a vector representing the macroeconomic variables, dividend yield, default spread, term spread, and the yield on the three-month T-bill. The model parameters are estimated using data from time $t-1$ through $t-60$. A minimum of two years of data is required for estimating the parameters. t-statistics are reported in parenthesis. The column titled "% > 0" gives the percentage of P10 − P1 that are positive, and p-values from the sign test measuring deviations from 50 percent are given in parentheses below the percentage positive.

	Non-Jan		Jan		Overall	
	P10 − P1	% > 0	P10 − P1	% > 0	P10 − P1	% > 0
			Panel A: Raw Payoffs			
7/26–12/94	0.61	66.45	0.22	61.76	0.58	66.06
	(6.85)	(0.00)	(0.65)	(0.07)	(6.68)	(0.00)
7/26–12/50	0.14	58.15	−0.82	50.00	0.06	57.48
	(0.75)	(0.01)	(−1.16)	(1.00)	(0.35)	(0.01)
1/51–6/63	0.91	78.83	1.00	92.31	0.92	80.00
	(9.70)	(0.00)	(3.29)	(0.00)	(10.27)	(0.00)
7/63–12/94	0.87	68.01	0.70	58.06	0.85	67.20
	(7.30)	(0.00)	(1.49)	(0.47)	(7.39)	(0.00)
			Panel B: Predicted-return Adjusted Payoffs			
1/53–12/94	−1.64	47.19	−5.60	30.95	−1.97	45.83
	(−2.42)	(0.24)	(−2.34)	(0.02)	(−3.01)	(0.07)
1/53–6/63	−4.45	43.48	−5.52	27.27	−4.55	42.06
	(−3.30)	(0.19)	(−1.22)	(0.23)	(−3.53)	(0.09)
7/63–12/94	−0.71	48.41	−5.62	32.26	−1.11	47.09
	(−0.91)	(0.59)	(−1.97)	(0.07)	(−1.47)	(0.28)

both 1/53–6/63 and 7/63–12/94, although it is statistically insignificant in the latter period.[21] Thus, similar to the case of individual stocks, payoffs to an industry momentum strategy are also negative once industry returns are adjusted for the predictability associated with macroeconomic variables.

[21] Statistical tests reject the null hypothesis that the unexplained portion of momentum payoffs is equal across subperiods.

I. Individual Stock Momentum: Industry Effect or an Independent Effect?

Our results thus far suggest that both individual stock momentum and industry momentum are related to the macroeconomy. Moskowitz and Grinblatt (1999) argue that momentum in individual stock returns is subsumed by momentum in industry returns. Hence, we analyze whether the relationship between individual stock momentum and macroeconomic variables merely reflects the relationship of the individual stock momentum to industry momentum. We do this by first investigating whether industry momentum fully explains individual stock momentum and then by testing whether the individual stock momentum, after controlling for industry effects, can be explained by our standard set of macroeconomic variables.

To study whether industry momentum fully explains individual stock momentum, we follow Moskowitz and Grinblatt and analyze payoffs to a momentum strategy based on industry-adjusted stock returns. During the formation period, we obtain the difference between the individual stock returns and their industry returns and use these industry-adjusted returns to assign stocks to portfolios. Panel A of Table IX reports the raw returns to the momentum strategy based on industry-adjusted returns.[22] The results show that, even after adjusting for industry returns, the average momentum payoff from buying winners and selling losers is significantly positive in the post-1951 period. The payoff from the industry-adjusted momentum strategy is 0.76 percent in the 1/51–6/63 period and 0.56 percent in the 7/63–12/94 period. This result is in contrast to Moskowitz and Grinblatt (1999), who use the top 30 percent and the bottom 30 percent to determine the momentum payoffs, and who also use Nasdaq stocks in their sample. However, it is consistent with the conclusions of Grundy and Martin (2001) that industry momentum and individual stock momentum are distinct and independent effects.

Panel B of Table IX reports the payoffs to industry-adjusted momentum portfolios that are adjusted for the predicted returns obtained from the one-period-ahead forecasts from the business-cycle model of equation (1). This analysis is similar to the one presented in Panel A, except that now we control for differences in predicted returns during the holding period. Thus, the momentum deciles are formed based on the industry-adjusted stock returns in the six-month formation period, and Panel B presents the average return adjusted for the predicted return during the following six-month period. Similar to the results presented in Table III, the average unexplained returns are negative but insignificant in the period 1/53–12/94. This result is stable across subperiods and suggests that the earlier findings of a relationship between individual stock momentum and lagged macroeconomic variables are not driven by the industry component of the stock returns.

[22] We have also conducted this analysis using industry-adjusted returns in the holding period, and qualitatively our results remain unchanged.

Table IX

Payoffs from a Momentum Strategy Based on Industry-adjusted Returns

For each month t, all NYSE–AMEX stocks i on the monthly CRSP tape are ranked into decile portfolios according to their industry-adjusted returns during the period $t-6$ through $t-1$. For each firm i and for each month t, the industry-adjusted returns are computed as the stock returns in excess of the industry returns. Decile portfolios are formed monthly by weighting equally returns of all firms in that decile ranking. The momentum strategy designates winners and losers as the bottom (P1) and top (P10) portfolios and takes a long position in portfolio P10 and a short position in portfolio P1. The positions are held for the following six-month period (t through $t+5$). Panel A shows the strategy's raw monthly payoffs during the holding period, while Panel B shows the holding period payoffs after adjusting for predicted returns. Predicted returns are the one-period-ahead forecast returns (not including the intercept) from the following model: $R_t = \alpha + \beta \boldsymbol{X_{t-1}} + e_t$, where $\boldsymbol{X_t}$ is a vector representing the macroeconomic variables, dividend yield, default spread, term spread, and the yield on the three-month T-bill. The model parameters are estimated using data from time $t-1$ through $t-60$. A minimum of two years of data is required for estimating the parameters. t-statistics are reported in parenthesis. The column titled "% > 0" gives the percentage of P10 − P1 that are positive, and p-values from the sign test measuring deviations from 50 percent are given in parentheses below the percentage positive.

	Non-Jan		Jan		Overall	
	P10 − P1	% > 0	P10 − P1	% > 0	P10 − P1	% > 0
Panel A: Raw Payoffs						
7/26–12/94	0.83	65.78	−6.72	17.65	0.20	61.80
	(4.19)	(0.00)	(−6.58)	(0.00)	(0.96)	(0.00)
7/26–12/50	0.01	56.67	−6.80	16.67	−0.54	53.40
	(0.02)	(0.03)	(−4.20)	(0.00)	(−1.20)	(0.27)
1/51–6/63	1.17	72.26	−3.51	15.38	0.76	67.33
	(5.58)	(0.00)	(−2.91)	(0.02)	(3.16)	(0.00)
7/63–12/94	1.33	70.32	−8.00	19.35	0.56	66.14
	(6.07)	(0.00)	(−4.54)	(0.00)	(2.02)	(0.00)
Panel B: Predicted-return Adjusted Payoffs						
1/53–12/94	−0.78	47.62	−15.30	33.33	−1.99	46.43
	(−0.56)	(0.33)	(−3.40)	(0.04)	(−1.48)	(0.12)
1/53–6/63	−2.48	43.48	−11.20	36.36	−3.24	42.86
	(−1.13)	(0.19)	(−1.31)	(0.55)	(−1.52)	(0.13)
7/63–12/94	−0.21	48.99	−16.76	32.26	−1.57	47.62
	(−0.12)	(0.75)	(−3.13)	(0.07)	(−0.95)	(0.38)

As a robustness check, we have regressed the raw payoffs from industry-adjusted momentum strategy on lagged macroeconomic variables, using the past five years of data, and use the estimated parameters to predict the one-month-ahead payoffs. The unexplained return (RES) for each month is then calculated as the estimated intercept plus the prediction error. The time-series averages of the intercept (INT) and the payoff that is unexplained by lagged macroeconomic variables (RES) are both negative during the period 1/52–12/94. The coefficients on default spreads are significantly negative during 7/63–12/94, whereas the coefficients on term spreads and on three-month T-bills yields are significantly positive during both the subperiods 1/52–6/63 and 7/63–12/94. These results (available upon request) are qualitatively similar to the results reported in Table IV and suggest that the relationship between individual stock returns and the macroeconomy is distinct and independent from the relationship between industry returns and the macroeconomy.

III. Discussion and Interpretation

The empirical analysis thus far shows that momentum in individual stock returns and in industry returns is attributable primarily to a common set of macroeconomic variables. We now interpret our results in the context of a simple model for decomposition of momentum profits.

Consider the following multifactor linear process for stock returns:

$$r_{it} = \mu_{it} + \sum_{k=1}^{L} \beta_{ik} f_{kt} + \sum_{m=1}^{M} \theta_{im} z_{mt} + e_{it}, \tag{2}$$

where r_{it} is the return on security i, μ_{it} is the expected return on security i conditional on the information set at time t, f_{kt} is the return on the factor mimicking portfolio k (e.g., the Fama–French factors), β_{ik} is the factor loading of security i on factor k, e_{it} is the firm-specific component of return, z_{mt} represents industry portfolio returns orthogonal to the returns on the factor-mimicking portfolios, and θ_{im} is stock i's sensitivity to the return on industry m. By construction, the K factor portfolios, the industry components, and the idiosyncratic terms are contemporaneously uncorrelated. We also assume

$$E(f_{lt} f_{kt-1}) = 0, \text{ for all } l \neq k;$$

$$E(e_{it} e_{jt-1}) = 0, \text{ for all } i \neq j;$$

$$E(z_{mt} z_{nt-1}) = 0, \text{ for all } m \neq n;$$

$$E(z_{mt} f_{kt-h}) = 0, \text{ for all } m, k \text{ and } h = \pm 1;$$

$$E(e_{it} f_{kt-h}) = 0, \text{ for all } i, k \text{ and } h = \pm 1;$$

$$E(e_{it} z_{mt-h}) = 0, \text{ for all } i, m \text{ and } h = \pm 1;$$

where $E(e_{it}) = 0$ for all i, and $E(z_{mt}) = 0$ for all m. The above serial correlation structure in factor, industry, and stock returns generates a simple decomposition of momentum profits in equations (4) and (5) below.

Given the above return structure, we can now obtain returns to the momentum strategy of buying winners and selling losers. We will follow the standard methodology of forming equally weighted decile winner and loser portfolios based on the past six months of returns and hold the self-financing portfolio that is long winners and short losers for the next six months. For this momentum strategy to be profitable, past winners have to continue to outperform and past losers have to continue to underperform. In other words:

$$E[(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})] > 0, \tag{3}$$

where a bar over a variable denotes its cross-sectional average. The above cross-sectional covariance equals the expected profits from the zero-cost trading strategy that weights stocks by their past returns less the past equally weighted return. For expositional simplicity, we will decompose returns to the above weighted relative strength strategy instead of decomposing the returns to the equally weighted decile portfolios. Based on the assumed return-generating process, the momentum profits can be decomposed as follows:

$$\begin{aligned} E[(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})] = {} & (\mu_{it} - \bar{\mu}_t)(\mu_{it-1} - \bar{\mu}_{t-1}) \\ & + \sum_{k=1}^{L} (\beta_{ik} - \bar{\beta}_k)^2 \operatorname{Cov}(f_{kt}, f_{kt-1}) \\ & + \sum_{m=1}^{M} (\theta_{im} - \bar{\theta}_m)^2 \operatorname{Cov}(z_{mt}, z_{mt-1}) \\ & + \operatorname{Cov}(e_{it}, e_{it-1}). \end{aligned} \tag{4}$$

Averaging over all N stocks, the momentum profits equal

$$\begin{aligned} & \frac{1}{N}\sum_{i=1}^{N} (\mu_{it} - \bar{\mu}_t)(\mu_{it-1} - \bar{\mu}_{t-1}) + \sum_{k=1}^{L} \sigma_{\beta_k}^2 \operatorname{Cov}(f_{kt}, f_{kt-1}) \\ & \quad + \sum_{m=1}^{M} \sigma_{\theta_m}^2 \operatorname{Cov}(z_{mt}, z_{mt-1}) + \frac{1}{N}\sum_{i=1}^{N} \operatorname{Cov}(e_{it}, e_{it-1}), \end{aligned} \tag{5}$$

where $\sigma_{\beta_k}^2$ and $\sigma_{\theta_m}^2$ are the cross-sectional variances of the portfolio loadings and the industry sensitivities, respectively.

There are four sources of momentum profits suggested by equation (5). The first term, $(\mu_{it} - \bar{\mu}_t)(\mu_{it-1} - \bar{\mu}_{t-1})$, represents contribution to momentum profits due to the expected returns. As long as the conditionally expected return of stock i is higher (or lower) than the cross-sectional mean, both in the formation period, $t - 1$, and in the holding period, t, the momentum strategy of buying winners and selling losers will result in positive profits. The second term, $\sum_{k=1}^{L}\sigma_{\beta_k}^2 \operatorname{Cov}(f_{kt}, f_{kt-1})$, represents the contribution due to the serial correlation in the factors. If the factor portfolio returns exhibit positive serial correlation, the momentum strategy will tend to pick stocks with high βs when the conditional expectation of the factor portfolio return is high. The third term, $\sum_{m=1}^{M}\sigma_{\theta_m}^2 \operatorname{Cov}(z_{mt}, z_{mt-1})$, represents the contribution to momentum profits due to the serial correlation in the industry return components, and the last term, $\operatorname{Cov}(e_{it}, e_{it-1})$, is the serial correlation in the firm-specific components.

To varying degrees, evidence supporting or contradicting the above four alternative sources of momentum profits has been presented in the literature. Conrad and Kaul (1998) show that cross-sectional dispersion in mean returns (assuming constant expected returns) can potentially generate the observed profits to the momentum strategy. However, Jegadeesh and Titman (2001) and Grundy and Martin (2001) show that unconditional expected returns are incapable of explaining momentum and argue that serial correlation in the firm-specific components is the origin of the momentum profits. In contrast, Moskowitz and Grinblatt (1999) show that momentum profits are attributable primarily to serial correlation in industry portfolios. They show that industry momentum is highly profitable even after controlling for cross-sectional dispersion in mean returns and that the industry momentum subsumes momentum in individual stock returns. However, Grundy and Martin (2001) show that the industry momentum and the individual stock momentum are distinct and separate phenomena, with each strategy being profitable on its own.

We now discuss our empirical results in the context of the four sources of the momentum profits as per equation (5). Our analysis as well as that in Grundy and Martin (2001) shows that, while there is strong momentum in industry portfolios, the individual stock and the industry momentum returns are distinct and separate phenomena. The irrational underreaction and/or the behavioral arguments generally suggest that momentum profits have to be driven by the serial covariation in the firm-specific returns. However, in Section II.F, we find that the momentum payoffs are not driven by the unexplained portion of returns (from our business cycle model). Also, as a further test of the importance of serial covariation in explaining momentum, in Appendix B, we calibrate the serial correlation (ρ) in the firm-specific component of returns using a simple return-generating process. Our calibration indicates that there is no plausible value of ρ that is consistent with the conjecture that momentum profits are being driven by the idiosyncratic component of returns. Thus, it is unlikely that firm-specific underreaction to information results in momentum profits.

As regards the covariation in factors as source of momentum, both Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999) reject serial covariation in the factors as a source of the momentum profits. They have found almost zero serial covariation in consecutive nonoverlapping six-month returns on the equally weighted index as well as on the Fama–French factor mimicking portfolios. However, it still might be the case that we have not yet identified the cross-sectional risk factors correctly. While it is entirely possible that momentum is driven by the serial covariation in these as yet unidentified risk factors, we focus on the first term in equation (5).

We believe that the evidence in this paper is consistent with time-varying expected returns being a plausible explanation for stock momentum. To the extent that the predictability of stock returns by macroeconomic variables is due to the ability of these variables to capture time-varying risk, our results suggest that the profitability of momentum payoffs arises from the cross-sectional differences in conditionally expected returns. Under this interpretation, our results support the arguments of Conrad and Kaul (1998) and Berk et al. (1999) that systematic variation in expected returns, across momentum portfolios, accounts for the profitability of momentum strategies.

If the above argument that short-term return continuations are a manifestation of the cross-sectional variations in expected returns is correct, and if expected returns are relatively stable around the formation period, then these profits should continue to obtain in different measurement periods around the formation period.[23] Lack of such evidence would cast doubt on risk-based explanations for momentum and would be inconsistent with our arguments in Sections II.F and II.G, that momentum is driven by persistence in the predicted component of returns. We test this conjecture by examining the payoffs to momentum portfolios in the measurement period lagged 6 months after the formation period and in the 12 months prior to the formation period. Table X presents the results from this analysis.

Panel A of Table X presents the momentum strategy payoffs when there is a gap of six months between the formation period ($t - 6$ through $t - 1$) and the measurement period ($t + 6$ through $t + 11$). The average payoffs from buying winners and selling losers are a significant 0.49 percent per month during the period 1/51–6/63 and 0.67 percent per month during 7/63–12/94. Thus, the momentum payoffs based on past six-month returns continue to be profitable for a year following the formation period. This finding is consistent with the evidence presented in Jegadeesh and Titman (1993). Panel B of Table X presents the results when returns are measured in the six-month period ($t - 12$ through $t - 7$) prior to the formation period ($t - 6$ through $t - 1$). Interestingly, the payoffs to momentum portfolios are significantly positive during the preformation period as well. The monthly return differential between the winner and the loser portfolios is 0.79 percent in 1/51–6/63 and 0.59 percent in 7/63–12/94. Moreover, from Panel C, we observe that the return differential persists even when a gap of six months is allowed between the formation period ($t - 6$ through $t - 1$) and the return measurement period ($t - 18$ through $t - 13$). The magnitude of the payoffs in the preformation period is relatively stable irrespective of whether returns are measured in the six months immediately preceding the formation period or after allowing for a gap of six months. Further, we are unable to reject the null hypothesis that the momentum payoffs in the various return

[23] We thank Gene Fama for suggesting this.

Table X

Momentum Strategy Payoffs in Different Holding Periods

For each month t, all NYSE–AMEX stocks on the monthly CRSP tape with returns for months $t-6$ through $t-1$ are ranked into decile portfolios according to their return during the period $t-6$ through $t-1$. Decile portfolios are formed monthly by weighting equally all firms in that decile ranking. The momentum strategy designates winners and losers as the top (P10) and bottom (P1) portfolios and takes a long position in portfolio P10 and a short position in portfolio P1. The mean payoffs for the period $t+6$ through $t+11$ (Panel A), for the period $t-12$ through $t-7$ (Panel B), and for the period $t-18$ through $t-13$ (Panel C) are presented for these portfolios. t-statistics are reported in parentheses. The column titled "% > 0" gives the percentage of P10 − P1 that are positive, and p-values from the sign test measuring deviations from 50 percent are given in parentheses below the percentage positive.

	Non-Jan		Jan		Overall	
	P10 − P1	% > 0	P10 − P1	% > 0	P10 − P1	% > 0
Panel A: Return Measurement Period is $t+6$ Through $t+11$						
1/27–12/94	0.83	67.38	−4.97	26.47	0.35	63.97
	(4.28)	(0.00)	(−5.46)	(0.00)	(1.72)	(0.00)
1/27–12/50	0.27	66.29	−4.75	37.50	−0.15	63.89
	(0.56)	(0.00)	(−2.60)	(0.31)	(−0.33)	(0.00)
1/51–6/63	0.84	69.34	−3.23	15.38	0.49	64.67
	(4.77)	(0.00)	(−4.11)	(0.02)	(2.48)	(0.00)
7/63–12/94	1.25	67.44	−5.86	22.58	0.67	63.76
	(6.36)	(0.00)	(−4.24)	(0.00)	(2.84)	(0.00)
Panel B: Return Measurement Period is $t-12$ Through $t-7$						
1/26–6/94	0.45	62.33	−1.18	44.12	0.32	60.83
	(3.48)	(0.00)	(−1.69)	(0.40)	(2.38)	(0.00)
1/26–12/50	−0.06	57.41	−2.79	41.67	−0.28	56.12
	(−0.19)	(0.02)	(−2.05)	(0.54)	(−0.94)	(0.04)
1/51–6/63	0.84	73.72	0.23	46.15	0.79	71.33
	(6.71)	(0.00)	(0.47)	(1.00)	(6.45)	(0.00)
7/63–6/94	0.69	61.67	−0.51	45.16	0.59	60.32
	(4.77)	(0.00)	(−0.48)	(0.72)	(3.73)	(0.00)
Panel C: Return Measurement Period is $t-18$ Through $t-13$						
1/26–12/93	0.44	60.08	1.61	64.71	0.54	60.46
	(3.86)	(0.00)	(1.99)	(0.02)	(4.32)	(0.00)
1/26–12/50	0.24	55.19	1.87	58.33	0.38	55.44
	(0.94)	(0.10)	(0.89)	(0.54)	(1.28)	(0.07)
1/51–6/63	0.47	64.23	1.00	69.23	0.52	64.67
	(3.30)	(0.00)	(1.81)	(0.27)	(3.73)	(0.00)
7/63–12/93	0.58	62.25	1.68	67.74	0.67	62.70
	(4.44)	(0.00)	(2.23)	(0.07)	(4.95)	(0.00)

measurement periods are different from each other. These results provide corroborating evidence for our earlier arguments that stock momentum is a result of the persistence in the predicted component of returns. The profitability of momentum strategies in both the preformation and postformation periods is consistent with momentum payoff representing reward for risk: The stocks with high (low) returns during the formation and measurement periods are those that have higher (lower) expected returns, and this cross-sectional variation in expected returns drives the momentum profits.

Notwithstanding the above, a proponent of behavioral theories can argue that the predictive ability of macroeconomic variables arises from irrational shifts in optimism or pessimism about the underlying economy and that the relationship between momentum payoffs and macroeconomic variables captures the irrationality of investors in interpreting macroeconomic data. However, given that momentum payoffs are observed for as long as 12 months after (and before) the formation period, theories based on underreaction to common factors would imply an extremely slow price reaction process to common information. Further, this interpretation of our results raises the question as to why investors misinterpret macroeconomic information and not firm-specific information.

IV. Conclusions

The finance literature has struggled with the Jegadeesh and Titman (1993) result of excess returns to buying winners and selling losers. These momentum returns have been widely documented in international data, and continue to exist in the U.S. data. Moreover, this momentum anomaly has so far defied risk-based explanations. A number of researchers have put forth behavioral theories suggesting that investor psychological biases in the reaction to information may be causing systematic underreaction, resulting in the continuation of short-term returns. However, the persistence of momentum returns long after the anomaly has been widely disseminated suggests that behavioral theories may not provide the full picture. Consistent and persistent underreaction should provide low-risk arbitrage opportunities to rational investors, who can hold a diversified portfolio that is long on winners and short on losers and which is constructed to have low factor risk.

The main contribution of this paper is to provide a possible role for rational pricing theories to explain momentum payoffs. This paper analyzes the relative importance of common factors and firm-specific information as sources of momentum profits. We show that profits to momentum strategies are explained by a parsimonious set of macroeconomic variables that are related to the business cycle. The evidence in this paper is consistent with time-varying expected returns being a plausible explanation for stock momentum. To the extent that the predictability of stock returns by macroeconomic variables is due to the ability of these variables to capture time-varying returns, our results suggest that the profitability of momentum payoffs arises from the cross-sectional differences in conditionally expected returns. These findings are consistent with the arguments of Berk et al. (1999) that profitability of momentum strategies represents compensation for bearing time-varying risk and, hence, is not inconsistent with rational pricing theories.

Although the ability of macroeconomic variables to predict stock returns is consistent with these variables capturing time-varying expected returns, this could also be interpreted as indicating commonality in investors' behavior across markets and with the overall economy. These alternative interpretations of predictability of stock returns have long been debated in the finance literature, and the precise source of predictability is still contested. Although we interpret our results as consistent with the role of time-varying expected returns in explaining momentum payoffs, most of our findings could as easily be interpreted to be consistent with theoretical models of investor irrationality. For instance, models based on investors' cognitive biases could be interpreted, in the light of our findings, as primarily related to investors' interpretation of macroeconomic shocks rather than firm-specific news, suggesting that irrational bubbles are correlated across assets. However, these arguments raise the intriguing question as to why investors interpret with a bias only macroeconomic information and not stock-specific information. Nonetheless, deciding whether return predictability is the result of rational variation in expected returns or irrational bubbles is never clear-cut.

The results presented in this paper suggest that future attempts to understand the sources of momentum can focus on identifying the risk factors that are predicted by macroeconomic variables. Fama's (1991) statement that "we should deepen the search for links between time-varying expected returns and business conditions, as well as for tests of whether the links conform to common sense and the predictions of asset pricing models" (p. 1585) continues to be relevant.

Appendix A

Derivation of Equation (1)

This appendix motivates our empirical specification in the context of asset pricing models with multiple betas. Expected returns, at each date, are related to the conditional covariances of returns with a measure of marginal utility, the pricing kernel. A linear, multivariate proxy for the pricing kernel results in a multibeta model that describes expected returns. A multibeta model asserts the existence of expected risk premiums $\lambda_{kt}(\boldsymbol{X_{t-1}})$, $k = 1, \ldots K$ such that expected returns, conditional on information $\boldsymbol{X_{t-1}}$, can be written as

$$E(R_{it}|\boldsymbol{X_{t-1}}) = \lambda_0 + \sum_k b_{ik}\lambda_{kt}(\boldsymbol{X_{t-1}}), \tag{A1}$$

where b_{ik} are the betas (multiple regression coefficients) of the R_{it} on K state variables.[24]

Following Ferson and Harvey (1991) and He et al. (1996), we use lagged values of the value-weighted market dividend yield, default spread, term spread, and yield on three-month T-bills as the instrumental variables ($\boldsymbol{X_{t-1}}$) to obtain time-varying expected returns. The conditional risk premium for any factor, k, is written as a linear function of the instrumental variables:

$$\lambda_{kt} = a_{k0} + a_{k1}DIV_{t-1} + a_{k2}YLD_{t-1} + a_{k3}TERM_{t-1} + a_{k4}DEF_{t-1}. \tag{A2}$$

Using the linear conditional risk premium in (A2) to rewrite the expected returns in (A1) yields the specific model used in this paper. The predicted return is the one-period-ahead forecast from the following regression equation:

$$R_{it} = c_{i0} + c_{i1}DIV_{t-1} + c_{i2}YLD_{t-1} + c_{i3}TERM_{t-1} + c_{i4}DEF_{t-1} + e_{it}, \tag{A3}$$

where $c_{i0} = \lambda_0 + \sum_k b_{ik}a_{k0}$ and $c_{ij} = \sum_k b_{ik}a_{kj}$, for $j > 0$.

Appendix B

Momentum and Underreaction to Firm-specific Information

By decomposing returns into a predicted portion and the unexplained portion in Sections II.F and II.G, we have argued that momentum profits do not result from underreaction to firm-specific information but are captured by predicted returns from the business cycle model. In this appendix, we further test whether momentum payoffs arise due to underreaction to firm-specific information. We examine the amount of serial correlation in firm-specific returns needed to generate the observed persistence in momentum payoffs. Using a simple decomposition of momentum payoffs, we calibrate the serial correlation in firm-specific returns required to explain momentum. The model used is simple so as to focus on the serial covariation in stock-specific returns. In the paper, we present a more comprehensive model to identify the source of the momentum profits.

To derive the decomposition of momentum payoffs, consider the following simple factor model for stock returns:

$$r_{it} = \mu_i + \sum_k b_{ik} f_{kt} + e_{it}, \tag{B1}$$

where r_{it} is the return on security i in period t, μ_i denotes the expected return on stock i, f_{kt} represents risk factor k, b_{ik} is the factor loading of stock i on factor k, and e_{it} is the firm-specific component of return in period t.

[24] The above expected return model is also consistent with APT, where the risk premia on the K-factors are predicted by the state variables, $\boldsymbol{X_{t-1}}$. In the APT framework, λ_0 is the risk-free rate.

Additionally, we assume zero serial correlation in the factors. Following Lo and MacKinlay (1990) and Jegadeesh and Titman (1995), we use the following relative strength momentum portfolio weights:

$$w_{it} = +(r_{it-1} - \bar{r}_{t-1})/N, \tag{B2}$$

where N is the number of stocks and $\bar{r}_{t-1}$ represents the equally weighted index return at time $t - 1$. The time t profit of this momentum strategy is given by

$$\Pi_t = 1/N \sum_i^N (r_{it-1} - \bar{r}_{t-1}) r_{it}, \tag{B3}$$

and the time $t + 1$ profit is

$$\Pi_{t+1} = 1/N \sum_i^N (r_{it-1} - \bar{r}_{t-1}) r_{it+1}. \tag{B4}$$

Let $\mathrm{corr}(e_{it}, e_{it-1}) = \rho$. Then, upon taking expectations,

$$E(\Pi_t | e_{it-1}) = \sigma_\mu^2 + (\rho/N) \sum_i^N e_{it-1}^2 \tag{B5}$$

and

$$E(\Pi_{t+1} | e_{it-1}) = \sigma_\mu^2 + (\rho^2/N) \sum_i^N e_{it-1}^2. \tag{B6}$$

Taking differences between the above expected profits:

$$\Delta\Pi \equiv E(\Pi_t | e_{it-1}) - E(\Pi_{t+1} | e_{it-1}) = [\rho(1 - \rho)/N] \sum_i^N e_{it-1}^2, \tag{B7}$$

where e_{it} is the firm-specific component of return in period t, $\rho = \mathrm{corr}(e_{it}, e_{it-1})$, and N represents the number of securities. Thus, if there is to be any decay, over time, in the expected momentum profits due to correction in the underreaction to a firm-specific component of returns, then $\Delta\Pi > 0$, which is possible only if $0 < \rho < 1$. Let us now consider the data.

For the period 7/63–12/94, the payoffs from relative strength strategies are 0.34 percent in the six-month holding period immediately following the formation period (i.e., t through $t + 5$) and 0.30 percent in the following six-month period (i.e., $t + 6$ through $t + 11$). Similarly, in the period immediately preceding the formation period ($t - 7$ through $t - 12$) the payoff to this strategy is 0.36 percent, while it is 0.32 percent in the six-month period prior to this ($t - 13$ through $t - 18$). These suggest that $\Delta\Pi$ is an economically and statistically insignificant four basis points for our sample of NYSE–AMEX stocks.[25] This implies that if the autocorrelation, ρ, has to be in the range $0.95 > \rho > 0.05$, then $\sum_i^N(e_{it-1}^2/N)$ has to be less than 0.008, which is implausibly small for six-month stock returns. In fact, the estimate of $\sum_i^N(e_{it-1}^2/N)$ varies from 0.07 to 0.10, depending on whether the mean is assumed constant over time or the CAPM is used to measure the error terms. Since the values of ρ suggested by these estimates are implausible, serial covariation in the firm-specific component of returns is unlikely to be an explanation for stock momentum.

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[25] These results are also consistent with those in Table X, which shows momentum payoffs to be relatively stable in various return measurement periods around the formation period.

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