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Two Essays on Momentum

Seung-Chan Park
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Seung-Chan Park entitled "Two Essays on Momentum." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

Phillip Daves, Major Professor

We have read this dissertation and recommend its acceptance:

James W. Wansley, Michael C. Ehrhardt, Halima Bensmail

Accepted for the Council:
Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

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Two Essays on Momentum

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Seung-Chan Park
December 2005

DEDICATION

This dissertation is dedicated to my wife, Eun-Soo Oh,

my daughters, You-Jeong and Ho-Jeong Park,

my parents, Wan-Yang Park and Kew-An Rim,

and my parents-in-law, Il-Hwan Oh and In-Han Kim,

for always believing in me, inspiring me, and encouraging me to reach higher

in order to achieve my goals.

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Abstract

One of the most controversial topics in recent investment literature has been stock return momentum. If an investor buys past winners and sells past losers, he will earn positive profits in the intermediate-term horizon (3 to 12 months). While behavioral theories seem to dominate as an explanation for the momentum phenomenon since momentum has been regarded as direct counter evidence for the efficient market hypothesis, Chordia and Shivakumar (2002) find that momentum can be explained by a set of macroeconomic variables. Chordia and Shivakumar argue that momentum is caused by time-varying expected returns that can be predicted by a set of macroeconomic variables, which might be associated with time-varying risk.

However, the first essay of my dissertation shows that even if the macroeconomic variables are independent of stock returns, they can appear to predict momentum profits if they exhibit high persistence and the momentum portfolio period overlaps with the parameter estimation period. I am able to produce results similar to those of Chordia and Shivakumar with randomly generated variables, while I show that once the parameter estimation periods are changed, the predictive power of the macroeconomic variables for momentum disappear. My results provide evidence that the predictive power of the macroeconomic variables comes from a spurious relation between stock returns during the momentum portfolio formation period and predicted returns from the macroeconomic variables. My results further suggest that Chordia and Shivakumar's argument that the

predictive power of macroeconomic variables for momentum is a challenge to behavioral theories is indeed premature.

The second essay shows that the ratio of the 50-day moving average to the 200-day moving average has significant predictive power for future returns. Stocks with a high moving average ratio tend to outperform stocks with a low moving average ratio for the next six months. This predictive power is distinct from that of the nearness of the current price to the 52-week high, which was first documented by George and Hwang (2004). The moving average ratio, combined with the nearness to the 52-week high, can explain most of the intermediate-term momentum profits. This suggests that an anchoring bias in which investors use moving averages and the 52-week high as their reference points for estimating fundamental values is the main source of momentum effects. Momentum profits caused by the anchoring bias do not disappear in the long-run, confirming George and Hwang's argument that intermediate-term momentum and long-term reversals are separate phenomena.

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Part 1. Dissertation Introduction

Recent research indicates that past stock returns have predictive power for future returns over three investment horizons. First, Lehmann (1990) and Jegadeesh (1990) document short-term return reversals. Stocks that have performed well for the past one week (one month) tend to perform poorly in the next one week (one month) while stocks that have performed poorly for the past one week (one month) tend to perform well in the next period. Second, Jegadeesh and Titman (1993) show that intermediate-term momentum strategies produce significantly positive profits. An intermediate-term momentum strategy buys stocks that have performed well and sells stocks that have performed poorly over the previous 3 to 12 months and holds this position for the next 3 to 12 months. Finally, DeBondt and Thaler (1985), Lee and Swanminathan (2000), and Jegadeesh and Titman (2001) show that there are long-term (3- to 5-years) return reversals.

At first glance, the predictable patterns in stock returns seem to be inconsistent with even the weak-form efficient market hypothesis. For example, the CAPM or Fama-French three-factor model fails to explain momentum profits. (See Jegadeesh (1990), Fama and French (1996) and Grundy and Martin (2001)) This has lead to the recent development of behavioral models to explain the momentum phenomenon under which return continuation is caused by positive autocorrelation of firm-specific components in returns. (See Barberis, Shleifer, and Vishny (BSV, 1998), Daniel, Hirshleifer, and Subrahmanyam (DHS, 1998), and Hong and Stein (HS, 1999)) However, Chordia and Shivakumar (2002) show that once stock returns are adjusted for their predicted returns from a set of macroeconomic variables, there is no momentum and argue that the momentum is caused by the predicted portion of returns from the macroeconomic variables. In other words, a momentum strategy tends to buy stocks when their expected returns are high and sell when their expected returns are low and the time-varying expected returns can be predicted by the macroeconomic variables. They further argue that if the macroeconomic variables are associated with time-varying risk of stocks, then momentum can be consistent with the efficient market hypothesis, even though the risk factors associated with the macroeconomic variables are not yet identified.

However, in Part 2 of this dissertation I show that random variables that have first-order autocorrelation similar to the true macroeconomic variables appear to explain momentum profits just like Chordia and Shivakumar's true macroeconomic variables. Also, the predictive power of the macroeconomic variables for momentum disappears when the parameter estimation periods are modified so that the momentum portfolio formation period and parameter estimation period are completely disjoint. I also show analytically and through a *Monte Carlo* simulation method that a hypothetical macroeconomic variable that follows a positive autoregressive process should appear to explain the momentum profits even if it is independent of stock returns. These empirical results and analyses suggest that the predicted power of the macroeconomic variables for momentum documented by Chordia and Shivakumar (2002) come from a spurious relation between stock returns over the momentum portfolio formation period and the predicted returns from the persistent macroeconomic variables.

Part 3 of this dissertation addresses issues among behavioral models for momentum. Most behavioral models attribute momentum to investors' biases in judgment under uncertainty, such as conservatism or overconfidence reinforced by self-attribution, or market inefficiency caused by slow diffusion of information. However, George and Hwang (2004) find that the nearness of the current price to the 52-week high price can explain a large portion of the momentum profits and argue that investors use the 52-week high as their reference against which they evaluate the potential impact of news. In addition to the nearness to the 52-week high, I find a moving average ratio – the ratio of 50-day moving average price to 200-day moving average price – has significant predictive power for future returns and that past returns on which conventional momentum strategies are based on have little predictive power for future returns in the intermediate horizon once returns are controlled for the returns forecasted by the nearness to the 52-week high and the moving average ratio. I interpret this as evidence that investors suffer from an anchoring bias in which they use the moving average price as a reference point when they estimate a stock's current fundamental value.

Part 2. Spurious Predictive Power of Persistent Macroeconomic Variables for Momentum

I. Introduction

Ever since Jegadeesh and Titman (1993) documented profits from intermediate-term momentum strategies, the financial literature has struggled to explain the source of the profits. One line of research has been to explain momentum as a result of investors' irrationality; a number of models based on investors' irrationality have been developed along this line. (See, Barberis, Shleifer, and Vishny, (1998) Daniel, Hirshleifer, and Subrahmanyam, (1998) Hong and Stein, (1999) and Barberis and Shleifer, (2003))[1] Another line of research has suggested that momentum profits can be consistent with the efficient market hypothesis. For example, Conrad and Kaul (1998) show that intermediate-term momentum profits mainly come from the cross-sectional dispersion of unconditional expected returns of stocks, while Jegadeesh and Titman (2001) argue that the results in Conrad and Kaul are driven by estimation errors in the estimation of unconditional expected returns. Also, Berk, Green, and Naik (1999) develop a theoretical model that predicts intermediate term momentum profits. In their model, time-varying but persistent systematic risk generates momentum profits.

In line with Berk, Green and Naik (1999), Chordia and Shivakumar (2002) (hereafter CS) show that a set of macroeconomic variables that are popular in finance literature can explain a six-month/six-month momentum profit. The macroeconomic variables that CS use are dividend yield (*DIV*), default spread (*DEF*), the yield on three-month *T*-bills (*YLD*) and the term structure spread (*TERM*).[2] CS show that once adjusted for one-

[1] Details of the behavioral models are in Part 3 of the dissertation.
[2] Detailed definitions of these variables are in the next section.

month-ahead predicted returns from the set of macroeconomic variables, stock returns do not exhibit momentum. Even though CS do not show the relationship between the macroeconomic variables and systematic risk factors, their results have important implications for both behavioral theories and conventional asset pricing theories. Most behavioral explanations for momentum focus on the time-series predictability of firm-specific stock returns that cannot be explained by any common factors. However, CS's findings suggest that momentum profits may not come from firm-specific returns, but from different sensitivities of stocks to the time-varying macroeconomic variables. If the macroeconomic variables are assumed to be related to systematic risk factors, momentum profits can come from time-varying systematic risks among individual stocks, and this would be consistent with the efficient market hypothesis. Therefore CS argue the natural next study should focus on identifying risk factors that are related to the macroeconomic variables.

In this study, I investigate CS's methodology and conclusions. I argue that the reason that the macroeconomic variables appear to explain the six-month/six-month momentum profits is because of the spurious relation between these highly persistent macroeconomic variables and the already documented return continuations in the intermediate horizon. First, I show that even if the macroeconomic variables are independent of stock returns for all lags but are highly persistent, stocks that performed well for the previous six months would tend to have high one-month-ahead predicted returns based on the macroeconomic variables, and stocks that performed poorly for the previous six months would tend to have low one-month-ahead predicted returns. Augmented Dickey-Fuller tests on each time-series of the four macroeconomic variables show that I may not reject the null hypothesis that each of the macroeconomic variables has a unit root. This suggests that all of the macroeconomic variables are highly persistent, even if they do not follow random walk processes. Second, I show that if momentum portfolio formation periods are excluded from the parameter estimation periods, the macroeconomic variables do not have any predictive power for momentum. Also, I show that randomly generated macroeconomic variables that have similar first-order autoregressive coefficients appear to explain the intermediate-term momentum phenomenon as well as the true macroeconomic variables do. Finally, I show why a momentum strategy based on previous predicted returns from the macroeconomic variables can produce higher profits than a traditional momentum strategy based on past raw returns.

The remainder of this paper is organized as follows. The next section reviews the literature related to this study including Chordia and Shivakumar (2002). Section III describes the macroeconomic variables that I use and discusses the possible effects of differences from those that CS used, and in Section IV, I present my methodology and empirical findings. Finally, Section V concludes.

II. Literature Review

II.A. Explanations and theories for intermediate-term momentum

Explanations and theories for intermediate-term momentum based on behavioral assumptions well outnumber those based on the rational expectation hypothesis and consistent with the efficient market hypothesis. Three of the explanations and theories consistent with the efficient market hypothesis are Conrad and Kaul (1998), Berg, Green, and Naik (1999) and Chordia and Shivakumar (2002). However, Jegadeesh and Titman (2002) show that Conrad and Kaul's empirical tests suffer from small sample biases and methodological adjustments for the biases reverses the Conrad and Kaul's findings.

In the theoretical model of Berg et al., the value of a firm is the sum of the value of its existing assets and the value of growth options. Under this model, expected stock returns are determined jointly by the average systematic risk of the firm's existing assets, the current interest rate, and the relative importance of ongoing projects to growth opportunities in the firm's value. Berg et al. define the systematic risk of a project to be negatively proportional to the covariance between the unexpected change in cash flows and the unexpected change in the pricing kernel for the project. The pricing kernel for a project is positively related to current interest rate, therefore interest rates affect the systematic risk of existing projects. Also, in their model, the sensitivity of the value of existing projects to a change in interest rates is smaller than the sensitivity of the value of the growth options. For this reason, a mature firm may be affected less by interest rate changes.

The average systematic risk of a firm's existing assets is time-varying since the firm may undertake new projects and some projects die off, but it is highly persistent, since the collection of ongoing projects does not change dramatically over short time periods. This may give theoretical foundation to CS's study. The basic premise of CS is that stock returns are related to the one-month lagged macroeconomic variables including interest rates, the return on each firm has different sensitivities to the macroeconomic variables, and finally the sensitivities of returns the macroeconomic variables are time-varying. The macroeconomic variables CS use are dividend yield, default spread, yield on three-month T-bills, and term structure spread. The dividend yield (*DIV*) is 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; the default spread (*DEF*) is defined as the difference between the average yield on bonds rated BAA by Moodys and the average yield of bonds with a Moodys rating of AAA; the term structure 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 Treasury bills that mature in three months.

CS include the yield on the three-month T-bill (*YLD*) 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 has been shown to be associated with slow mean reversion in stock returns across several economic cycles (Keim and Stambaugh, 1986, Campbell and Shiller, 1988, and Fama and French, 1988) This variable 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. Fama and French (1988) show that default premiums (*DEF*) track long-term business cycle conditions and document the fact that this variable is higher during recessions and lower during expansions. Fama and French also show that the term spread (*TERM*) is closely related to the short-term business cycles.

II.B. Review of Chordia and Shivakumar (2002)

The predicted return is the one-month-ahead forecast from the following business cycle model;

$$r_{it} = c_{i0} + c_{i1}DIV_{t-1} + c_{i2}YLD_{t-1} + c_{i3}TERM_{t-1} + c_{i4}DEF_{t-1} + e_{it}, \quad (1)$$

where r_{it} is return on stock i for month t and $DIV_{t\text{-}1}$, $YLD_{t\text{-}1}$, $TERM_{t\text{-}1}$, and $DEF_{t\text{-}1}$ are realizations of the macroeconomic variables at the end of month t-1. The parameters of the model, c_{ij}, are estimated each month, for each stock, using the previous 60 months of returns. The parameters of the model are then used to obtain the one-month-ahead predicted return for each stock. Using the business cycle model specified in equation (1), CS conducted various tests to show that profits to a six-month/six-month momentum strategy can be explained by the predicted returns from the four macroeconomic variables and payoffs to the momentum strategy disappear once stock returns are adjusted for their predictability based on the business cycle model. The summary of procedures and the results of the critical tests follow.

II.B.1 Momentum payoffs after adjusting for predicted returns

II.B.1.a) Definitions and methodologies

CS mainly investigate the six-month/six-month momentum strategy. Under this strategy, all stocks are sorted in ascending order based on their previous six-month returns at month t. Stocks in the top decile are assigned to portfolio $P1_t$, the stocks in the next decile are assigned to portfolio $P2_t$, and so on. The momentum strategy invests an equal amount of money in the stocks in portfolio $P10_t$ and sells short stocks in portfolio $P1_t$ at month t. If there are N stocks in the market, the weight vector of the momentum portfolio that is constructed at the beginning of month t can be represented as

$\dot{\mathbf{w}}_t = [\dot{w}_{1t} \quad \cdots \quad \dot{w}_{Nt}]' \cdot (10/N)$, where ()′ indicates the transpose of a matrix, and where

$\dot{w}_{it} = 1$ if $i \in P10_t$, $\dot{w}_{it} = -1$ if $i \in P1_t$ and $\dot{w}_{it} = 0$ otherwise. Since the momentum strategy holds this position for next six months, the weight vector for the momentum strategy at the beginning of month t is the sum of weight vectors of portfolios constructed from $t-5$ to t divided by six.

Definition 1 "A six-month/six-month momentum strategy (shortly momentum strategy throughout this paper)": Under this trading strategy, the weight vector for the momentum portfolio at the beginning of month t, denoted as $\mathbf{w}_t$, is defined as $\mathbf{w}_t = \sum_{j=0}^{5} \dot{\mathbf{w}}_{t-j} (1/6)$.

If I denote $\mathbf{r}_t$ to be a vector of return realizations for month t, $\mathbf{r}_t = [r_{1t} \quad \cdots \quad r_{Nt}]'$, then the month-$t$ raw profit from this momentum strategy, π_t, can be written as

$$\pi_t \equiv \mathbf{w}_t' \mathbf{r}_t. \tag{2}$$

Let's denote $\mathbf{z}_t$ to be a vector of realizations of the macroeconomic variables at the end of month t, $[DIV_t \quad TERM_t \quad YLD_t \quad DEF_t]$, and $\mathbf{x}_t$ to be $[1 \quad \mathbf{z}_t]$. At the beginning of month t, CS regress stock i's return on the one-month lagged macroeconomic variables as in regression equation (1) using data from t-T to t-1 in order to estimate the parameters. Let's denote $\hat{\mathbf{c}}_t$ to be the OLS estimate vector of the parameters at month t so

$\hat{\mathbf{c}}_{it} = \begin{bmatrix} \hat{c}_{it}^0 & \hat{c}_{it}^1 & \hat{c}_{it}^2 & \hat{c}_{it}^3 & \hat{c}_{it}^4 \end{bmatrix}'$. The one-month-predicted return for stock *i* for month *t* used by CS, denoted by $\hat{r}_{it}$, can be written as

$$\hat{r}_{it} = \mathbf{x}_{t-1}\hat{\mathbf{c}}_{it} . \tag{3}$$

Also if $\hat{\mathbf{r}}_t$ is defined to be a vector of the one-month-ahead predicted returns of all stocks in the market for month *t*, $\hat{\mathbf{r}}_t = \begin{bmatrix} \hat{r}_{1t} & \cdots & \hat{r}_{Nt} \end{bmatrix}'$, then the month-*t* predicted (one-month-ahead) profit from the six-month/six-month momentum strategy can be defined as follows.

Definition 2 "The predicted momentum profit (from the macroeconomic variables) for month t": the predicted momentum profit for month t, denoted $\hat{\pi}_t$, is the one-month-ahead predicted return on the momentum portfolio defined in Definition 1. So $\hat{\pi}_t \equiv \mathbf{w}_t'\hat{\mathbf{r}}_t$.

Sometimes CS predict stock returns without estimates of intercepts, $\hat{c}_{it}^0$, so I define the estimate of the coefficient vector without intercept, denoted as $\hat{\mathbf{c}}_{it}^{\circ}$, to be $\begin{bmatrix} \hat{c}_{it}^1 & \hat{c}_{it}^2 & \hat{c}_{it}^3 & \hat{c}_{it}^4 \end{bmatrix}'$. The one-month-ahead predicted return without intercept for stock *i* for month *t*, $\hat{r}_{it}^{\circ}$, is

$$\hat{r}_{it}^{\circ} = \mathbf{z}_{t-1}\hat{\mathbf{c}}_{it}^{\circ} . \tag{4}$$

Notice that $\hat{c}_{it}^1$, $\hat{c}_{it}^2$, $\hat{c}_{it}^3$, and $\hat{c}_{it}^4$ in vector $\hat{\mathbf{c}}_{it}^{\circ}$ are estimates of the regression coefficients for the equation that includes the intercept, i.e. $r_{it} = c_{0i} + \sum_{k=1}^{4} c_{ik} z_{kt-1} + e_{it}$, not for the equation that excludes intercept, i.e. $r_{it} = \sum_{k=1}^{4} c_{ik} z_{kt-1} + e_{it}$. CS describe the reason for this as follows: "*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".*[3]

Defining $\hat{\mathbf{r}}_t^{\circ}$ to be $\left[\hat{r}_{1t}^{\circ} \quad \cdots \quad \hat{r}_{Nt}^{\circ}\right]'$, then the month-*t* (one-month-ahead) predicted profit without intercept from the six-month/six-month momentum strategy can be defined as follows.

Definition 2′ "Predicted momentum profit (from the macroeconomic variables) without intercepts for month t": Predicted momentum profit without intercepts for month t, denoted $\hat{\pi}_t^{\circ}$, is the one-month-ahead predicted return without intercepts on the momentum portfolio defined in Definition 1. So $\hat{\pi}_t^{\circ} \equiv \mathbf{w}_t'\hat{\mathbf{r}}_t^{\circ}$.

Definitions 3 and 3′ follow as:

Definition 3 "Predicted-return-adjusted momentum profit with intercepts for month t": The adjusted momentum profit for predicted returns with intercepts for month t,

[3] Page 994 in Chordia and Shivakumar (2002).

denoted as π_t^a, is the difference between the raw momentum profit and the predicted momentum profit. So $\pi_t^a \equiv \pi_t - \hat{\pi}_t$, where π_t is defined in Equation (2) and $\hat{\pi}_t$ is defined in Definition 2.

Definition 3′ "Predicted-return-adjusted momentum profit without intercepts for month t": The adjusted momentum profit for predicted returns without intercepts for month t, denoted $\pi_t^{\circ a}$, is defined to be $\pi_t^{\circ a} \equiv \pi_t - \hat{\pi}_t^{\circ}$, where π_t is defined in Equation (2) and $\hat{\pi}_t^{\circ}$ is defined in Definition 2′.

II.B.1.b) Findings

CS calculate the time-series average of adjusted momentum profits for predicted returns without intercepts, $\pi_t^{\circ a}$ in Definition 3′, over the three sample periods, 1/53-12/94, 1/53-6/63, and 7/63-12/94.[4] CS estimate parameters to Equation (1) using the previous 60 months of observations, so that $T = 60$. When they calculate one-month-ahead predicted return for stock *i* for month *t*, first they estimate the parameters in Equation (1) using stock *i*'s return series from *t*-*T* to *t*-1 and the time-series of the macroeconomic variables from *t*-*T*-1 to *t*-2. Then the one-month-ahead predicted return for month *t* is calculated based on the macroeconomic variables at *t*-1 and the estimated parameters. The estimated intercept is excluded from the equation for predicted return. The difference between the

[4] CS also calculate one-month-ahead predicted returns using Equation (1) including a January dummy. Their results with January dummy are essentially same as those without a January dummy.

actual return and the predicted return on the momentum portfolio is called the predicted-return-adjusted momentum profit.

The time-series average of the predicted-return-adjusted momentum profits without intercepts defined in Definition 3, $\pi_t^{\circ a}$**,** is -1.94 percent per month (*t*-statistic is -1.41) over the entire sample period, -3.70 percent (*t*-statistic is -1.62) from 1/53 to 6/63, and -1.36 percent (*t*-statistic is -0.81) from 7/63 to 12/94. All of the adjusted profits are negative but statistically insignificant. CS argue that these results suggest that stock returns for the previous six months do not predict the portion of future returns that is unexplained by the business cycle model, and that the predictive ability of past returns is restricted to the portion of returns that is predictable by macroeconomic variables. Therefore, momentum can be explained by the macroeconomic variables.

II.B.2 Role of predicted and stock-specific returns in causing momentum

II.B.2.a) Definitions and methodology

CS create two additional six-month/six-month momentum strategies. They are momentum strategies based on stock-specific returns and predicted returns. Under these two strategies, for each stock *i* and for each month *t*, the one-month-ahead predicted return without intercept, $\hat{r}_{it}^{\circ}$, is calculated as in Equation (4). The stock-specific return for stock *i* for month *t*, $r_{it}^{\circ s}$, is defined to be the difference between the realized return and the one-month-ahead predicted return without intercept for month *t*, i.e. $r_{it}^{\circ s} = r_{it} - \hat{r}_{it}^{\circ}$. Under the momentum strategy based on the stock-specific returns, at the beginning of each month *t*, all stocks are sorted based on their compounded previous six-month stock-specific returns. The weight vector for this momentum portfolio constructed at time *t* can be written as $\dot{\mathbf{w}}_t^{\circ s} = \left[\dot{w}_{1t}^{\circ s} \quad \cdots \quad \dot{w}_{Nt}^{\circ s}\right]' \cdot (10/N)$, where $\dot{w}_{it}^{\circ s} = 1$ if stock *i*'s compounded six-month stock-specific return belongs to the top ten percent, $\dot{w}_{it}^{\circ s} = -1$ if stock *i*'s previous six-month stock-specific return belongs to the bottom ten percent and $\dot{w}_{it}^{\circ s} = 0$ otherwise.

In contrast, under the momentum strategy based on predicted returns, at the beginning of each month *t*, all stocks are sorted based on their one-month-ahead predicted returns without intercept during the previous six months. The weight vector is written as $\dot{\mathbf{w}}_t^{\circ p} = \left[\dot{w}_{1t}^{\circ p} \quad \cdots \quad \dot{w}_{Nt}^{\circ p}\right]' \cdot (10/N)$, where $\dot{w}_{it}^{\circ p} = 1$ if stock *i*'s six-month one-month-ahead predicted return belongs to the top ten percent, $\dot{w}_{it}^{\circ p} = -1$ if stock *i*'s six-month one-month-ahead predicted return belongs to the bottom ten percent and $\dot{w}_{it}^{\circ p} = 0$ otherwise.

Definition 4 "A momentum strategy based on the stock-specific returns": Under this trading strategy, the weight vector for the momentum portfolio at beginning of month t, denoted as $\mathbf{w}_t^{\circ s}$, is defined to be $\mathbf{w}_t^{\circ s} = \sum_{j=0}^{5} \dot{\mathbf{w}}_{t-j}^{\circ s} (1/6)$.

Therefore, the month-*t* profit from the momentum strategy based on the stock-specific returns, denoted $\pi_t^{\circ s}$, can be written as

$$\pi_t^{\circ s} \equiv \left(\mathbf{w}_t^{\circ s}\right)' \mathbf{r}_t . \tag{5}$$

Definition 5 "A momentum strategy based on predicted returns": Under this trading strategy, the weight vector for the momentum portfolio at the beginning of month t, denoted $\mathbf{w}_t^{p}$***, is defined to be*** $\mathbf{w}_t^{\circ p} = \sum_{j=0}^{5} \dot{\mathbf{w}}_{t-j}^{\circ p} (1/6)$**.**

In the same manner as before, the month-*t* profit from the momentum strategy based on predicted returns, denoted $\pi_t^{\circ p}$, can be written as

$$\pi_t^{\circ p} \equiv \left(\mathbf{w}_t^{\circ p}\right)' \mathbf{r}_t . \tag{6}$$

II.B.2.b) Findings

CS calculate time-series averages of the momentum strategies based on the stock-specific returns and predicted returns that are defined in Definitions 4 and 5. The time-series averages of the profits from the momentum strategy based on the stock-specific returns, $\pi_t^{\circ s}$ defined in Equation (5) are -0.06 percent (*t*-statistic is -0.44) over the entire sample period, 1/53-12/94, -0.35 percent (*t*-statistic is -1.79) from 1/53 to 6/63, and -0.03 percent (*t*-statistic is 0.18) from 7/63 to 12/94, showing that the profits from the momentum strategy based on the stock-specific returns are not significantly different from zero. In contrast, the time-series averages of the profits from the momentum strategy based on predicted returns, $\pi_t^{\circ p}$ are 0.48 percent (*t*-statistic is 2.70) over the entire sample period, 0.49 percent (*t*-statistic is 2.01) from 1/53 to 6/63, and 0.48 percent (*t*-statistic is 2.14) from 7/63 to 12/94. This shows that the profits from the predicted-return based momentum strategies are significantly positive. Regarding the business cycle model defined in Equation (1) as a multi-factor model similar to the Fama-French three-factor model, CS argue that these findings suggest that it is the time-varying expected returns and not the firm-specific returns that drive profits to the momentum strategy of buying winners and selling losers. This challenges behavioral models for momentum, since most behavioral models argue that the idiosyncratic component of returns produces the momentum phenomenon.

II.B.3 Predicted versus raw returns

Finally, CS test whether past returns that were predicted by the macroeconomic variables or past raw returns have more predictive power for future returns. Jegadeesh and Titman (1993) show that raw returns appear to have some predictive power for future returns in the intermediate-term horizon. Also, CS show that the macroeconomic variables can predict future returns as described in Subsection II.B.2. CS's findings described in II.B.2 might arise because the returns predicted by the macroeconomic variables are simply capturing the information contained in past returns. In order to show that this is not the case, CS do a horse race experiment.

II.B.3.a) Definitions and methodology

CS compare returns on two sets of 25 double-sorted portfolios. Under the first double-sorting scheme, denoted *RP*, at the beginning of each month t all stocks are sorted into quintiles according to 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 previous six-month predicted returns defined in Equation (3). In this test, CS include the intercepts.[5] In contrast, under the second double-sorting scheme, denoted *PR*, all stocks are first sorted into quintiles by their previous six-month predicted returns defined in Equation (3), then stocks in each quintile are sorted into quintiles based on their previous six-month raw returns. All 50 portfolios under *RP* and *PR* are held for the next six months. Therefore, the month-t return on each portfolio is the arithmetic average of the returns on six portfolios constructed from $t-5$ to t. CS calculate the time-series averages of monthly returns on the 50 equal-weight portfolios over the period from July 1963 to December 1994. These tests generate two 5×5 matrixes, whose components are the time-series averages of monthly returns on these equal-weight double-sorted portfolios. It is better to formally define the two resulting matrixes, since I can explain my own results in Section IV referring to these definitions.

Definition 6 "Matrix **RP*****": The resulting matrix from the double-sorting scheme RP. RP_{ij}, the $(i, j)^{th}$ component of*** **RP*****, represents the time-series average return on the portfolio constructed in the following manner. All stocks are first sorted into quintiles by their buy-and-hold raw returns over the prior six months. Stocks in the j^{th} quintile then assigned to one of five equal-sized portfolios based on their (one-month-ahead) predicted returns from a business cycle model compounded over the prior six months. (the 5^{th} quintile represents the highest previous raw or predicted returns)***

[5] CS do not provide the reason why they exclude the intercept in the previous tests and include the intercepts in this test.

Definition 7 "Matrix* PR*": The resulting matrix from the double-sorting scheme PR. PR_{ij}, the (i, j)th element of* PR*, represents the time-series average return on the portfolio constructed in the following manner. All stocks are first sorted into quintiles by their (one-month-ahead) predicted returns from the business cycle model compounded over the prior six months. Stocks in the jth quintile then assigned to one of five equal-sized portfolios based on their buy-and-hold returns over the prior six months.

Suppose that RP_{5j} is significantly greater than RP_{1j}. This means that within the j^{th} quintile based on previous raw returns, stocks with high predicted returns during the previous six months tend to outperform stocks with low past predicted returns. However, this, in itself, would not be evidence that past predicted returns have more predictive power for future returns than do past raw returns, since finer differentials in past returns within the j^{th} quintile may generate differentials in future returns. That's why CS do the second test. If at the same time PR_{i5} is not significantly greater than PR_{i1}, which means that within the i^{th} quintile based on past predicted returns, stocks with high past raw returns tend to have performance similar to that of stocks with low past raw returns, then this might be evidence that past predicted returns have more predictive power for future returns than do past raw returns. Combining the results from two different portfolio formation schemes might give some evidence for whether past predicted returns or past raw returns have more predictive power for future returns.

This test is important since the results might give evidence on which one, predicted returns or raw returns, can predict future returns. Both predicted returns from the macroeconomic variables and raw returns appear to have predictive power for future returns. However, if only raw returns are truly able to predict future returns but the predicted returns are somehow correlated to raw returns, then the predicted returns can appear to predict future returns.

II.B.3.b) Findings

CS calculate matrices **RP** and **PR** defined in Definitions 6 and 7 using the data from 7/63 to 12/94. CS first show that RP_{5j} is significantly greater than RP_{1j} for all j except for j = 1. This suggests that past predicted returns can predict future returns even after controlling for momentum based on past returns. However, PR_{i5} is significantly greater than PR_{i1} for only i = 5. This is interpreted by CS to mean that with the exception of the highest predicted return quintile, once controlled for their predicted returns, raw returns do not have further predictive power for future returns. Comparing matrixes **RP** and **PR** and with the findings described in the previous subsection, CS argue that the ability of past raw returns to predict future returns is due to information contained in the predicted components of returns and that momentum profits are attributable primarily to a common set of factors, rather than to firm-specific returns.

III. Data

One concern for this study is the dataset of macroeconomic variables. I failed to obtain the dataset that CS used in their 2002 paper. I used the dataset used in Pontiff and Schall (1998) and provided by Pontiff.[6] CS also seem to use the dataset provided by Pontiff, but it is not clear whether CS modified the dataset from Pontiff or whether Pontiff provided exactly the same dataset to CS and us. Pontiff and Schall (1998) show that all of the macroeconomic variables are highly persistent. Estimates of the first-order autocorrelations of *DIV*, *TERM*, *YLD* and *DEF* are 0.97, 0.97, 0.97 and 0.99 over the period from January 1926 to August 1994. Panel A of Table 2.1.[7] in this paper shows the autocorrelation estimates for the macroeconomic variables over the period from January 1951 to December 1994. All of the first-order autocorrelation coefficient estimates for the four macroeconomic variables are greater than 0.95 and they are decreasing very slowly as the orders increase. I also conducted augmented Dickey-Fuller tests of all of the macroeconomic variable series for the same period. Based on these tests, I may not reject the null hypothesis that these series have unit roots. Panel A and the Dickey-Fuller tests show that all of the macroeconomic variables are highly persistent. Panel B of Table 2.1 suggests that all of the macroeconomic variables are contemporaneously correlated to each other. For example, the estimate of the contemporaneous correlation coefficient between the dividend yield and the term structure spread is -0.21 and p-value under the null that the two macroeconomic variables are not correlated is less than 0.01%.

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[6] I thank Pontiff for kindly providing the dataset.
[7] All tables of this part of the dissertation are in Appendix 1.

In order to see whether my programs and dataset are similar to CS's, I replicated Table III of CS's 2002 paper. Table 2.2 presents CS's and my raw momentum profits and predicted-return-adjusted momentum profits for the sample periods, 1/53-12/94, 1/53-6/63, and 7/63-12/94. It also reports the momentum profits separately for non-January months, Januarys, and overall periods for each sample period for comparison purposes.[8] Momentum portfolios are constructed as in Definition 1, based on the previous six-month raw returns using all stocks traded on the NYSE and AMEX from the CRSP data files. Panel A presents the time-series average of monthly raw momentum profits, which are defined in Equation (2), during the sample periods and Panel B presents the time-series average of predicted-return-adjusted momentum profits, which are returns on the momentum portfolios adjusted for the predicted returns from the macroeconomic variables without intercepts as defined in Definition 3′. In Panel C, predicted returns are calculated using $r_{it} = c_{0i} + \sum_{k=1}^{4} c_{ik} z_{kt-1} + \theta \cdot Jandum + e_{it}$, instead of Equation (1). In Panel C, intercepts are also excluded from the predicted returns.

Panel A shows that there is little difference between CS's raw momentum profits and ours. For all months and for the entire sample period, the difference in means of the raw momentum profits is 0.02 percent (or 2.90 percent of CS' raw momentum profit) and the difference in *t*-statistics is 0.09 (or 3.05 percent of CS' *t*-statistic). Differences in means and *t*-statistics for the first and second subsamples are similar to those for the entire sample period. The small difference may come from differences in treating missing

[8] In addition to Table 2.2, I replicate CS's Table VII with my macroeconomic variables and present the results in Table 2.10.

observations in momentum portfolio formation and in holding periods. In this particular case, predicted returns can be calculated for stocks that have at least 24 observations during the previous 60 months. The difference between CS raw momentum profits and ours may also come from different treatments of stocks that have enough observations to be included in momentum portfolios but insufficient observations for calculating predicted returns. Since CS do not describe such details in their paper, it is hard to replicate their tests exactly. I include in momentum portfolios all stocks that have six months of previous observations and calculate holding period returns using stocks for which predicted returns can be calculated, i.e. stocks that have at least 24 observations during the previous 60-month period. If some stocks in momentum portfolios do not meet the observation requirement for predicted returns, I replace the returns on the stocks with the average of the portfolio. My raw profits are similar to those of CS and the small differences should not significantly affect my arguments in the rest of this paper.

However, Panels B and C of Table 2.2 show that my results for adjusted momentum profits for predicted returns are different from those of CS. For instance, in Panel B where predicted returns are calculated without the January dummy, the difference in mean predicted-return-adjusted momentum profit is 0.36 percent (or 18.56 percent of CS's predicted-return-adjusted momentum profit) and the difference in *t*-statistic is 0.28 (or 19.86 percent of CS' *t*-statistic) for all months for the entire sample period. The differences in other sample periods are similar to those for the entire sample period and these differences seem significant compared to the differences in Panel A. Little differences in raw momentum profits between CS' and ours and large differences in predicted-adjusted momentum profits suggest that the macroeconomic variables that I have may be different from those used by CS.[9]

However, these differences do not affect my tests and arguments in this paper for two reasons. First, CS would draw exactly the same conclusions from my results in Table 2.2 as they draw from their results. All of the predicted-return adjusted momentum profits in Panels B and C of Table 2.2 have the same sign and statistical significance as those of CS except for one case (fifth row and first column in Panel B). And even in that case, both CS' and my results are not statistically significant. Second and more importantly, as I mention in Section I and will describe further in Section IV, even random variables that have similar first-order autocorrelation to the macroeconomic variables that I have can produce qualitatively the same results as CS.

IV. Methodology and Empirical Findings

IV.A. Predicted momentum profits when the macroeconomic variables are independent of stock returns

This subsection shows how spurious correlation between past raw returns and one-month-ahead predicted returns defined in Equations in (3) and (4)[10] can appear to explain momentum profits, even if the macroeconomic variables are independent of stock returns. Specifically, I show that even if the macroeconomic variables are independent of individual stock returns at all lags and individual stock returns follow white noise

[9] I tried to replicate Table III of CS (2002) in several different ways, but I failed to further reduce differences between CS' and my results.
[10] In the rest of this paper, (one-month-ahead) predicted return means (one-month-ahead) predicted return from the macroeconomic variables as defined in Equations (3) and (4).

processes, past six-month returns can still be positively correlated with one-month-ahead predicted returns. Therefore, the explanatory power of the macroeconomic variables for momentum profits may come from a spurious relation between past six-month returns and one-month-ahead predicted returns.

To demonstrate this result, first denote $\mathbf{z}_t$ to be a vector of realizations of the macroeconomic variables used in CS at the end of month t, i.e. $\mathbf{z}_t = \begin{bmatrix} DIV_t & TERM_t & YLD_t & DEF_t \end{bmatrix}$, and denote $\mathbf{x}_t$ to be $\begin{bmatrix} 1 & \mathbf{z}_t \end{bmatrix}$. Also, denote $\mathbf{Z}_t$ to be a $T \times 4$ matrix consisting of the time-series realizations of $\mathbf{z}$ over the T-month period, from $t - T + 1$ to t. Let $\mathbf{X}_t$ be a $T \times 5$ matrix $\begin{bmatrix} \boldsymbol{\iota} & \mathbf{Z}_t \end{bmatrix}$, where $\boldsymbol{\iota}$ is defined to be a $T \times 1$ vector of ones, $\begin{bmatrix} 1 & \cdots & 1 \end{bmatrix}'$. If I regress stock i's returns on the one-period lagged realizations of the macroeconomic variables using the previous T-period observations as specified in regression equation (1), the estimate of the regression coefficients at t is $\hat{\mathbf{c}}_{it} = \left(\mathbf{X}_{t-2}{}' \mathbf{X}_{t-2} \right)^{-1} \mathbf{X}_{t-2}{}' \mathbf{r}_{it-1}$, where $\mathbf{r}_{it-1} = \begin{bmatrix} r_{it-T} & \cdots & r_{it-1} \end{bmatrix}'$. As in Equation (3), the one-month-ahead predicted return on stock i for month t, $\hat{r}_{it}$, is $\mathbf{x}_{t-1} \hat{\mathbf{c}}_{it}$.

Now, consider the cross-sectional covariance between these one-month-ahead predicted returns and the cumulative returns over the prior m months, defined as

Definition 8: "Cross-sectional covariance between one-month-ahead predicted returns and the previous m-month cumulative returns at the beginning of month t":

$$\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right) = \frac{1}{N}\sum_{k=1}^{N}\left(\hat{r}_{it} - \overline{\hat{r}_t}\right)\left(r_{it-}^m - \overline{r_{t-}^m}\right),$$

where hats above variables indicate predicted returns, bars above variables indicate cross-sectional average, the superscript m and subscript t- jointly indicate the sum of returns for the m periods prior to month t. Therefore, $\overline{\hat{r}_t} = \frac{1}{N}\sum_{k=1}^{N}\hat{r}_{kt}$ ***,*** $\overline{r_{t-}^m} = \frac{1}{N}\sum_{k=1}^{N} r_{it-}^m$ ***,*** $r_{it-}^m = \sum_{j=1}^{m} r_{it-j}$ ***, where*** $\hat{r}_{it}$ ***is defined in Equation (3) and N is the number of stocks in the market.***

CS calculate predicted-return-adjusted momentum profits defined in Definition 3 by subtracting the predicted returns from the raw returns for stocks in the momentum portfolio and show that the predicted-return-adjusted momentum profits are not significantly different from zero. If this cross-sectional covariance, $\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)$, is positive at the beginning of month *t*, I can expect that the one-month-ahead predicted returns on winners during the previous *m* months are higher than those on previous losers, therefore the predicted-return-adjusted momentum profits are less than the raw momentum profits if I form momentum portfolios based on the previous *m*-month cumulative returns. Notice that I use the past cumulative returns over the momentum portfolio formation period as a measure of past performance for analytical convenience, while most momentum strategies, including CS', use the compounded returns. If the cross-sectional covariance between predicted returns and lagged returns is positive, part of the momentum profits can appear to be explained by the macroeconomic variables, no matter what causes the positive cross-sectional covariance. In the rest of this subsection, I will show that even if the macroeconomic variables are independent of stock returns at all lags, the cross-sectional covariance can be positive given the sample realizations of the macroeconomic variables.

In order to analyze the cross-sectional covariance when the macroeconomic variables are independent of stocks returns, I assume that monthly stock returns follows white noise processes and that they are independent of any of the macroeconomic variables and other stocks returns for all lags.

Assumption 1: All stock returns follow white noise processes and the processes are independent of any of the macroeconomic variables and other stocks' returns for all lags. So that

$$r_{it} = \varepsilon_{it}, \textit{ for } i = 1,\ldots,N,$$

where N is the number of stocks in the market and where $E(\varepsilon_{it}\varepsilon_{jt}) = 0$ ***for i ≠ j and*** $E(\varepsilon_{it}^2) = \sigma_i^2$ ***and*** $E(\varepsilon_{it}\varepsilon_{jt-s}) = 0$ ***for s ≠ 0.***

Assumption 1 precludes momentum profits that are already documented. However, I want to show in this subsection that even if the macroeconomic variables are independent of stocks returns, predicted momentum profits defined in Definitions 2 and 2′ can be positive. This will show adjusted momentum profits for predicted returns can be smaller than raw momentum profits. As will be discussed shortly, Assumption 1 is very simple so that I can derive expectations of predicted momentum profits under the independence assumption.

Next, let's consider the expectation of the cross-sectional covariance, defined in Definition 8, conditional on realizations of the macroeconomic variables up to month t-1, i.e. $E\left[\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)\middle|\Omega_{\mathbf{z}t-1}\right]$, where $E(\cdot|\cdot)$ means conditional expectation and $\Omega_{\mathbf{z}t-1}$ is the information set of realizations of the macroeconomic variables up to month t-1. The conditional expectation of the cross-sectional covariance between predicted returns and cumulative m-month lagged returns at time t can be written as

$$E\left[\left(\hat{r}_{it}-\overline{\hat{r}}_t\right)\left(r_{it-}^m-\overline{r_{t-}^m}\right)\middle|\Omega_{\mathbf{z}t-1}\right]=\frac{N-2}{N}E\left(\hat{r}_{it}r_{it-}^m\middle|\Omega_{\mathbf{z}t-1}\right)+\frac{1}{N^2}\sum_{k=1}^{N}E\left(\hat{r}_{kt}r_{kt-}^m\middle|\Omega_{\mathbf{z}t-1}\right)$$

$$=\frac{N-2}{N}\mathbf{x}_{t-1}\left(\mathbf{X}'_{t-2}\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}'_{t-2}E\left(\mathbf{r}_{it-1}r_{it-}^m\middle|\Omega_{\mathbf{z}t-1}\right)+\frac{1}{N^2}\mathbf{x}_{t-1}\left(\mathbf{X}'_{t-2}\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}'_{t-2}\sum_{k=1}^{N}E\left(\mathbf{r}_{kt-1}r_{kt-}^m\middle|\Omega_{\mathbf{z}t-1}\right)$$

$$=\frac{N-2}{N}\mathbf{x}_{t-1}\left(\mathbf{X}'_{t-2}\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}'_{t-2}E\left(\mathbf{r}_{it-1}r_{it-}^m\right)+\frac{1}{N^2}\mathbf{x}_{t-1}\left(\mathbf{X}'_{t-2}\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}'_{t-2}\sum_{k=1}^{N}E\left(\mathbf{r}_{kt-1}r_{kt-}^m\right),$$

because I assume that each of macroeconomic variables is independent of stock returns for all lags. If I denote $\boldsymbol{\iota}_m^*$ to be the $T\times 1$ vector whose first $(T-m)$ elements are zeros and whose remaining elements are ones, so that $\boldsymbol{\iota}_m^*=\begin{bmatrix}0 & \cdots & 0 & 1 & \cdots & 1\end{bmatrix}'$, it can be shown that

$$E\left(\mathbf{r}_{it-1}r_{it-}^m\right)=\boldsymbol{\iota}_m^*\sigma_i^2. \tag{7}$$

Therefore,

$$E\left[\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)\middle|\Omega_{\mathbf{z}t-1}\right]=\mathbf{x}_{t-1}\left(\mathbf{X}'_{t-2}\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}'_{t-2}\boldsymbol{\iota}_m^*\frac{1}{N}\sum_{i=1}^{N}\left[\frac{N-2}{N}\sigma_i^2+\frac{1}{N^2}\sum_{k=1}^{N}\sigma_k^2\right],$$

and since

$$\frac{1}{N}\sum_{i=1}^{N}\left[\frac{N-2}{N}\sigma_i^2+\frac{1}{N^2}\sum_{k=1}^{N}\sigma_k^2\right]=\frac{1}{N}\left(\frac{N-2}{N}\sum_{i=1}^{N}\sigma_i^2+\frac{1}{N}\sum_{k=1}^{N}\sigma_k^2\right)=\frac{N-1}{N^2}\sum_{k=1}^{N}\sigma_k^2 \ ,$$

it follows that

$$E\left[\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)\middle|\Omega_{\mathbf{z}t-1}\right]=A_t\Sigma \ , \tag{8}$$

where $A_t \equiv \mathbf{x}_{t-1}\left(\mathbf{X}_{t-2}'\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}_{t-2}'\boldsymbol{\iota}_m^*$ and $\Sigma \equiv \left(N-1\right)/N^2\sum_{k=1}^{N}\sigma_k^2$.

Notice that Equations (7) and (8) hold because of Assumption 1. This simplifying assumption allows us to easily estimate the sign of unconditional expectation of the cross-sectional covariance from the time-series average of the right-hand side of Equation (8) without further subjective assumptions regarding stock return processes. Since Σ in Equation (8) is positive, the sign of the conditional expectation of the cross-sectional covariance between predicted returns and the cumulative *m*-month lagged returns depends on the sign of A_t in Equation (8).

If the one-month-ahead predicted return excludes the intercept estimate as in Equation (4), as CS do in some of their analyses, the expectation of the cross-sectional covariance between the one-month-ahead predicted returns, denoted by $\hat{r}_{it}^{\circ}$ in Equation (4), and the past cumulative *m*-month returns, r_{it-}^m, conditional on realizations of the macroeconomic variables up to month *t*-1 is

$$E\left[\overline{\text{cov}}\left(\hat{r}_t^{\circ}, r_{t-}^m\right)\middle|\Omega_{\mathbf{z}t-1}\right]=\mathbf{z}_{t-1}\left[\mathbf{Z}_{t-2}'\left(\mathbf{I}-\frac{\boldsymbol{\iota}\boldsymbol{\iota}'}{T}\right)\mathbf{Z}_{t-2}\right]^{-1}\mathbf{Z}_{t-2}'\left(\mathbf{I}-\frac{\boldsymbol{\iota}\boldsymbol{\iota}'}{T}\right)\boldsymbol{\iota}_m^*\Sigma \ ,$$

and can be written as

$$E\left[\overline{\text{cov}}\left(\hat{r}_t^{\circ}, r_{t-}^{m}\right)\middle|\Omega_{\mathbf{z}t-1}\right] = B_t\Sigma ,$$

where I define $B_t \equiv \mathbf{z}_{t-1}\left[\mathbf{Z}'_{t-2}\left(\mathbf{I}-\frac{\mathbf{\iota\iota}'}{T}\right)\mathbf{Z}_{t-2}\right]^{-1}\mathbf{Z}'_{t-2}\left(\mathbf{I}-\frac{\mathbf{\iota\iota}'}{T}\right)\mathbf{\iota}_m^{*}$ and $\mathbf{I}$ is a $(T \times T)$ identity matrix.

Similarly, the conditional expectation of the cross-sectional covariance between intercept estimates and past cumulative m-month returns is

$$E\left[\overline{\text{cov}}\left(\hat{c}_{0t}, r_{t-}^{m}\right)\middle|\Omega_{\mathbf{z}t-1}\right] = C_t\Sigma ,$$

where $\hat{c}_0$ is the estimated intercept and

$$C_t \equiv \mathbf{\iota}'\left[\mathbf{I}-\mathbf{Z}_{t-2}\left(\mathbf{Z}'_{t-2}\mathbf{Z}_{t-2}\right)^{-1}\mathbf{Z}'_{t-2}\right]^{-1}\mathbf{\iota}'\left[\mathbf{I}-\mathbf{Z}_{t-2}\left(\mathbf{Z}'_{t-2}\mathbf{Z}_{t-2}\right)^{-1}\mathbf{Z}'_{t-2}\right]\mathbf{\iota}_m^{*} .$$

Under the momentum strategy used by CS, which is defined in Definition 1, momentum profits for month t are the arithmetic average of returns on m momentum portfolios that have been constructed based on returns from t-m+1 to t. Then the predicted momentum profit for month t, denoted $\hat{\pi}_t$ and defined in Definition 2, is also the arithmetic average of the predicted profits from m momentum portfolios. Therefore, the expected predicted momentum profit for month t conditional on $\Omega_{\mathbf{z}t-1}$, $E\left(\hat{\pi}_t\middle|\Omega_{\mathbf{z}t-1}\right)$, is proportional to the arithmetic average of the conditional expectation of the cross-sectional covariances between the one-month-ahead predicted returns at month t and the returns during the formation periods for the m momentum portfolios constructed from t-m+1 to t under Assumption 1. In other words,

$$E\left[\hat{\pi}_t \middle| \Omega_{\mathbf{z}t-1}\right] = \alpha \frac{1}{m}\sum_{j=0}^{m-1} E\left[\overline{\operatorname{cov}}\left(\hat{r}_t, r_{(t-j)-}^m\right) \middle| \Omega_{\mathbf{z}t-1}\right], \tag{9}$$

where α is some positive number and $r_{i(t-j)-}^m = \sum_{l=1}^m r_{it-j-l}$. Therefore, Equation (9) can be written as

$$E\left[\hat{\pi}_t \middle| \Omega_{\mathbf{z}t-1}\right] = \alpha \frac{1}{m}\sum_{j=0}^{m-1} A_t^j \Sigma = \beta \frac{1}{m}\sum_{j=0}^{m-1} A_t^j = \beta \mathrm{A}_t^m, \tag{10}$$

where β is some positive number and

$$\mathrm{A}_t^m \equiv \frac{1}{m}\sum_{j=0}^{m-1} A_t^j \text{ , and}$$

$$A_t^j \equiv \mathbf{x}_{t-1}\left(\mathbf{X}_{t-2}'\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}_{t-2}'\boldsymbol{\iota}_{m,j}^*,$$

and $\boldsymbol{\iota}_{m,j}^*$ is defined to be $T \times 1$ vector whose first (T-m-j) elements are zeros, whose next m elements are ones and the remaining elements are zeros.

Similarly, if I omit intercepts from the predicted momentum profits, then the conditional expectation of the predicted momentum profit, $\hat{\pi}_t^\circ$, on the realizations of the macroeconomic variables up to month t-1 can be written as

$$E\left[\hat{\pi}_t^\circ \middle| \Omega_{\mathbf{z}t-1}\right] = \beta \frac{1}{m}\sum_{j=0}^{m-1} B_t^j = \beta \mathrm{B}_t^m, \tag{11}$$

where

$$\mathrm{B}_t^m \equiv \frac{1}{m}\sum_{j=0}^{m-1} B_t^j \text{ , and}$$

$$B_t^j \equiv \mathbf{z}_{t-1}\left[\mathbf{Z}'_{t-2}\left(\mathbf{I}-\frac{\mathbf{\iota\iota}'}{T}\right)\mathbf{Z}_{t-2}\right]^{-1}\mathbf{Z}'_{t-2}\left(\mathbf{I}-\frac{\mathbf{\iota\iota}'}{T}\right)\mathbf{\iota}^*_{m,j}.$$

Also, the expectation of the difference between $\hat{\pi}_t$ and $\hat{\pi}_t^\circ$ conditional on the macroeconomic variables up to month t-1 can be written as

$$E\left[\hat{\pi}_t - \hat{\pi}_t^\circ \middle| \Omega_{\mathbf{z}t-1}\right] = \beta\frac{1}{m}\sum_{j=0}^{m-1}C_t^j = \beta \mathrm{X}_t^m = \beta\left(\mathrm{A}_t^m - \mathrm{B}_t^m\right), \tag{12}$$

where

$$\mathrm{X}_t^m \equiv \frac{1}{m}\sum_{j=0}^{m-1}C_t^j \text{, and}$$

$$C_t^j \equiv \mathbf{\iota}'\left[\mathbf{I}-\mathbf{Z}_{t-2}\left(\mathbf{Z}'_{t-2}\mathbf{Z}_{t-2}\right)^{-1}\mathbf{Z}'_{t-2}\right]^{-1}\mathbf{\iota}'\left[\mathbf{I}-\mathbf{Z}_{t-2}\left(\mathbf{Z}'_{t-2}\mathbf{Z}_{t-2}\right)^{-1}\mathbf{Z}'_{t-2}\right]\mathbf{\iota}^*_{m,j}.$$

Notice that $E\left[\hat{\pi}_t - \hat{\pi}_t^\circ \middle| \Omega_{\mathbf{z}t-1}\right]$ in Equation (12) is proportional to the conditional expectation of the cross-sectional covariance between the estimates of intercepts and stock returns during the momentum formation periods. In sum, Equations (10) and (11) show that under Assumption 1, the expectation of the predicted momentum profits conditional on the realizations of the macroeconomic variables up to the previous month are proportional to A_t^m if the intercept is included in predicting returns, and to B_t^m if the intercept is excluded from predicting returns. Equations (10) and (11) suggest that if the time-series averages of A_t^m and B_t^m during the sample period are positive, then time-series averages of the predicted momentum profits both with and without intercepts are also expected to be positive even if the macroeconomic variables are independent of stock returns under Assumption 1.

Table 2.3 shows the time-series averages and t-statistics of A_t^m, B_t^m, and X_t^m for $T = 60$ and $m = 6$ for the periods from 1/53 to 12/94, which is the same period over which CS calculate adjusted momentum profits for predicted returns as defined in Definitions 3 and 3′. Hereafter I drop the superscripts m for A_t^m, B_t^m, and X_t^m since m is fixed to be 6 for the rest of this subsection. Since I use the macroeconomic variables after January 1951 when T-bills rates start to vary freely as CS do, the values of A_t, B_t, and X_t are calculated with fewer than 60 months of data before January 1956. For example, if t = January 1953, then the values are calculated using only the previous 24 months of observations. After January 1956, I can calculate the values using the previous 60 months of observations. Therefore, I separately report time-series averages and t-statistics for A_t, B_t, and X_t for the period from January 1956 to December 1994.

The first row of Table 2.3 shows that both A_t and B_t are significantly positive over the entire sample period. This suggests that the time-series average of the momentum profits predicted by the macroeconomic variables with or without intercepts is expected to be positive even if the macroeconomic variables are independent of stock returns. Therefore, the time-series averages of the predicted-return-adjusted momentum profits defined in Definitions 3 and 3′ are expected to be less than the time-series average of the raw momentum profits under Assumption 1. In order to see the point, let's consider predicted-return-adjusted momentum profits, π_t^a. As defined in Definition 3, $\pi_t^a = \pi_t - \hat{\pi}_t$, where

π_t is raw momentum profit for month *t* and $\hat{\pi}_t$ is predicted momentum profit with intercepts. It can be shown that

$$E\left(\pi_t^a \middle| \Omega_{\mathbf{z}t-1}\right) = E\left(\pi_t \middle| \Omega_{\mathbf{z}t-1}\right) - E\left(\hat{\pi}_t \middle| \Omega_{\mathbf{z}t-1}\right).$$

Since $E\left(\hat{\pi}_t \middle| \Omega_{\mathbf{z}t-1}\right) = \beta \mathrm{A}_t$, where $\Omega_{\mathbf{z}t-1}$ is the realization of the macroeconomic variables up to month *t*-1 and β is some positive number, from Equation (10), and $E\left(\pi_t \middle| \Omega_{\mathbf{z}t-1}\right) = E(\pi_t)$ because momentum profits are independent of the macroeconomic variables under Assumption 1, and therefore, $E\left(\pi_t^a \middle| \Omega_{\mathbf{z}t-1}\right) = E\left(\pi_t^a \middle| \mathrm{A}_t\right)$, it follows that:

$$E\left(\pi_t^a \middle| \mathrm{A}_t\right) = E(\pi_t) - \beta \mathrm{A}_t.$$

Taking total expectations on both side of the above equation, it follows that

$$E\left(\pi_t^a\right) = E(\pi_t) - \beta E(\mathrm{A}_t). \tag{13}$$

Equation (13) and the fact that the time-series average of A_t is positive suggest that the time-series average of the predicted-return-adjusted momentum profits is expected to be less than the time-series average of the raw momentum profits.

Similarly, I can show that

$$E\left(\pi_t^{\circ a}\right) = E(\pi_t) - \beta E(\mathrm{B}_t)$$

where $\pi_t^{\circ a}$ is predicted-return-adjusted momentum profits without intercept, as defined in Definition 3′. The first row of Table 2.3 also shows that

$$\hat{E}(\mathrm{A}_t) > \hat{E}(\mathrm{B}_t),$$

where $\hat{E}(\cdot)$ means the time-series average. Therefore it follows that the time-series average of the predicted-return-adjusted momentum profits without intercepts is expected to be larger than that with intercepts. In other words, based on the fact that $\hat{E}(\mathrm{A}_t) > \hat{E}(\mathrm{B}_t)$, I expect that the unconditional expectation of the predicted-return-adjusted momentum profits without intercepts is greater than the unconditional expectation of the predicted-return-adjusted momentum profits with intercepts.

The second row shows that after January 1956 when most companies in the sample start to have 60 observations for parameter estimation, the *t*-statistic for A_t is more than 11 times higher than the *t*-statistic for B_t, while the average of A_t is only 1.27 times higher than that of B_t. This means that B_t has a higher standard error than A_t and implies that the standard error of conditional expectation of predicted momentum profits without intercepts on the lagged realizations of the macroeconomic variables is also higher than that with intercepts. This might suggests that the standard error of predicted-return-adjusted momentum profits without intercepts are higher than that with intercepts, since $\pi_t^{\circ a} = \pi_t - \hat{\pi}_t^{\circ}$ and $\pi_t^a = \pi_t - \hat{\pi}_t$. If it is the case, I expect that the absolute value of the *t*-statistic for predicted-return-adjusted momentum profits is smaller when I exclude intercepts from predicting returns than when I include intercepts, even if the mean predicted-return-adjusted momentum profits are the same.

Figure 2.1[11] show the values of A_t, B_t, and X_t for the period from January 1953 to December 1994. After January 1956, when most companies start to have 60 previous observations for estimating the parameters in Equation (1), B_t is much more volatile than A_t. This implies that under Assumption 1, the predicted momentum profits without intercepts, $\hat{\pi}_t^{\circ}$, are much more volatile than the predicted momentum profits with intercepts, $\hat{\pi}_t$. The values of A_t are negative in only 18 months out of the 528 months over the entire sample period (3.4 percent of the time), and 11 of the negative values come from the period before January 1956 until when the number of observation for estimating parameters is fewer than 60. In other words, even if stock returns are independent of the macroeconomic variables, the predicted momentum profits with intercept should be positive 99 percent of the time when I have 60 months of observations for estimating parameters of Equation (1). On the other hand, B_t is negative 204 months out of the total 504 months over the entire sample period. Therefore, if I define one-month-ahead predicted returns to exclude the intercept estimates, then predicted momentum profit should be negative 40 percent of the time.

Based on the findings in Table 2.3 and Figure 2.1, I expect to observe four empirical characteristics under Assumption 1, under which stock returns follow white noise processes and are independent of the macroeconomic variables and other stock returns for all lags.

[11] All figures of this part of the dissertation are in Appendix 1.

Prediction 1: Predicted-return-adjusted momentum profits defined in Definitions 3 and 3′ will be smaller than raw momentum profits on average.

This means that CS' findings, which are summarized in my Table 2.2, can be observed even when the macroeconomic variables have no predictive power for stock returns.

Prediction 2: Predicted-return-adjusted momentum profits with intercepts defined in Definition 3 will be larger than predicted-return-adjusted momentum profits without intercepts defined in Definition 3′.

This implies that if predicted-return-adjusted momentum profits with and without intercepts are negative on average as CS and I show in Table 2.2, then the average predicted-return-adjusted momentum profits without intercepts will be closer to zero than that with intercepts.

Prediction 3: Predicted momentum profits are much more volatile and the absolute value of the t-statistic for predicted-return-adjusted momentum profits is smaller when intercepts are excluded for predicting returns than when intercepts are included for prediction.

This is because standard error of B_t is much higher than the standard error of A_t and the sample mean of B_t is a little smaller than that of A_t as Table 2.3 suggests. This might suggest that mean value of predicted-return-adjusted momentum profits is smaller (in absolute value) and the standard error of predicted-return-adjusted momentum profits is higher when I exclude intercepts for predicting returns, leading to a smaller *t*-statistic.

Prediction 4: Predicted momentum profits will be negative about 3.5 percent of the time over the entire sample period if I include intercepts in predicting returns and about 40 percent of the time if I exclude intercepts.

IV.B. Raw and Predicted Momentum Profits

Figure 2.2 presents predicted momentum profits from the macroeconomic variables with and without intercepts over the sample period from January 1953 to December 1994. Predicted momentum profits are calculated as in Definitions 2 and 2′. At the beginning of each month *t*, momentum portfolios are constructed based on the previous six-month returns as in Definition 1. Returns on stocks in momentum portfolios are predicted by Equation (1), $r_{it} = c_{0i} + c_{1i}DIV_{t-1} + c_{2i}TERM_{t-1} + c_{3i}YLD_{t-1} + DEF_{t-1} + e_{it}$. Parameters are estimated using data from *t*-60 to *t*-1. The predicted momentum profit with intercepts, $\hat{\pi}_t$, for month *t* is the predicted return on the momentum portfolio for month *t*. The predicted momentum profit without intercepts, $\hat{\pi}_t^{\circ}$, is the predicted return on the momentum portfolio excluding intercept estimates.

Figure 2.2 shows that predicted momentum profits without intercepts are much more volatile than those with intercepts, which is consistent with Prediction 3. Also, visual investigation of Figures 1 and 2 suggests that the shapes of A_t and B_t are similar to those of predicted momentum profits with intercepts, $\hat{\pi}_t$, and predicted momentum profits without intercepts, $\hat{\pi}_t^{\circ}$, especially after January 1956. I will formally test the correlations between A_t and $\hat{\pi}_t$, and between B_t and $\hat{\pi}_t^{\circ}$ shortly.

Table 2.4 shows information similar to that in Table III in CS, but I add predicted momentum profits, $\hat{\pi}_t$ and $\hat{\pi}_t^{\circ}$, and predicted-return-adjusted momentum profits, π_t^a and $\pi_t^{\circ a}$, both with and without intercepts. Also, I present the average absolute deviation of raw momentum profits from predicted momentum profits. Panel A shows that the average predicted momentum profit with intercepts is larger (5.51 percent for the entire sample period) than that without intercepts (2.27 percent), therefore the average predicted-return-adjusted momentum profit with intercepts (-4.81 percent) is smaller than that without intercepts (-1.58 percent). This is consistent with Prediction 2 under Assumption 1. The average predicted-return-adjusted momentum profits without intercepts are -1.58 percent, -2.64 percent, and -1.23 percent per month for 1/53-12/94, 1/53-6/63, and 7/63-12/94, respectively. These numbers are closer to zero than those with intercepts, but still large in absolute terms relative to raw momentum profits, which are 0.71 percent, 0.89 percent, and 0.64 percent per month. However, none of the predicted-return-adjusted momentum profits without intercepts is statistically significant, while all of the raw momentum profits are statistically significant. This suggests that it is not only low sample mean but also large standard errors of the predicted momentum profits without intercepts that makes the absolute values of the *t*-statistics small. This is consistent with Prediction 3. Finally, the predicted momentum profits with intercepts are negative in 2.58 percent of the months for the entire sample period, while predicted momentum profits without intercepts are negative in 43.25 percent of the months, consistent with Prediction 4.

Panel A of Table 2.4 also shows that the average predicted momentum profit with intercept is 5.51 percent while the average raw momentum profit is only 0.71 percent, which means average predicted momentum profit is almost 8 times higher than average raw momentum profit. This suggests that the prediction error of the business cycle model used by CS is high on average and that the model may not accurately predict momentum profits. This is also true when predicted profits exclude intercepts. Panel B of Table 2.4 shows more obviously the inaccuracy of the business cycle model in predicting momentum profits. The average absolute deviations of raw momentum profits from predicted profits are 5.88 percent per month when intercepts are included in predicting returns and 23.44 percent per month when intercepts are excluded. This means that the average prediction error of the business cycle model without intercept for momentum profits is more than 33 times the mean value of the raw momentum profits. According to Panel B, the signs of the raw momentum profits and predicted momentum profits with intercepts are different in 33.13 percent of the months for the entire sample period, and most of the sign differences occur when the raw momentum profits are negative. This and the facts in Panel A suggest that predicted momentum profits with intercepts are almost always positive and higher than raw momentum profits, therefore, predicted-return-adjusted momentum profits with intercepts are almost always negative. When I exclude intercepts in predicting momentum returns, the signs of the raw momentum profits and predicted momentum profits are different in 46.43 percent of the months for the entire sample period. This suggests that the business cycle model without intercepts cannot predict even the sign of the momentum profits.

In order to see the relation between raw momentum profits and predicted momentum profits, I regress raw momentum profits on predicted momentum profits. In other words, I estimate the following two time-series regression equations.

$$\pi_t = \alpha_1 + \beta_1 \hat{\pi}_t + \eta_{1t}, \text{ and} \tag{14}$$

$$\pi_t = \alpha_2 + \beta_2 \hat{\pi}_t^{\circ} + \eta_{2t}, \tag{15}$$

where π_t is raw momentum profits defined in Equation (2) and $\hat{\pi}_t$ and $\hat{\pi}_t^{\circ}$ are predicted momentum profits with and without intercepts as defined in Definitions 2 and 2′. Panel A of Table 2.5 shows that the regression coefficients for Equations (14) and (15) are not significant at conventional significance levels. The *t*-statistics for β_1 and β_2 are -1.69 and -0.05, respectively. Also the R^2s are only 0.61 percent for Equation (14) and 0.00 percent for Equation (15). These results mean that the predicted momentum profits with or without intercepts are not correlated with raw momentum profits, and furthermore the macroeconomic variables have no predictive power for the time-series of the true momentum profits.

In the previous subsection, I showed that if the macroeconomic variables are independent of stock returns and stock returns follow white noise processes under Assumption 1, the expected predicted momentum profit with intercepts for month *t* conditional on realizations of the macroeconomic variables up to month *t*-1 is proportional to A_t, as in Equation (10), and the expectation of predicted momentum profit without intercepts is proportional to B_t, as in Equation (11). In order to see such correlations, I regress the predicted momentum profits with intercepts on A_t and the predicted momentum profits without intercepts on B_t, i.e., I estimate the following two time-series regression equations,

$$\hat{\pi}_t = \alpha_3 + \beta_3 \mathrm{A}_t + \eta_{3t}, \text{ and} \tag{16}$$

$$\hat{\pi}_t^{\circ} = \alpha_4 + \beta_4 \mathrm{B}_t + \eta_{4t}. \tag{17}$$

I estimate Equations (16) and (17) for the period from January 1956 to December 1994 during which I have 60 observations for each parameter estimation for the most of stocks. Panel B of Table 2.5 shows that the R^2s from regression (16) and (17) are 53 percent and 60 percent, respectively, and the *t*-statistics for both regression coefficients are significantly positive, 22.89 and 26.48. Therefore, I may conclude that a significant portion of predicted momentum profit forecasted by the macroeconomic variables can be explained by spurious prediction by the macroeconomic variables under the assumption that the macroeconomic variables are independent of stock returns.

IV.C. Persistence in Macroeconomic Variables

The results in the previous subsection suggest that the macroeconomic variables appear to explain momentum profits even if they are independent of stock returns. In this subsection, I investigate why the returns predicted by the four macroeconomic variables and lagged returns during momentum portfolio formation period are positively correlated, even when the macroeconomic variables are independent of stocks returns. High persistence of the macroeconomic variables plays a key role in this phenomenon. In the following subsections, I will introduce a simple hypothetical macroeconomic variable that is independent of stocks returns, analyze how the macroeconomic variable can appear to explain momentum profits and finally, using a *Monte Carlo* method, estimate expected cross-sectional covariance between predicted returns and previous six-month returns.

IV.C.1 A hypothetical macroeconomic variable and one-month-ahead predicted returns

For simplicity, I consider one hypothetical macroeconomic variable that follows a first order autoregressive process.

Assumption 2: A hypothetical macroeconomic variable, z, follows the following first order autoregressive process:

$$z_t = a_0 + az_{t-1} + \varepsilon_{zt}\text{, } \mathbf{0 < a < 1,}$$

where $E(\varepsilon_{zt}) = 0$ ***for all t and*** $E(\varepsilon_{zt}\varepsilon_{t-s}) = 0$ ***for*** $s \neq 0$ ***and*** $E(\varepsilon_{zt}^2) = \sigma_{\varepsilon z}^2$***. So the unconditional expectation of z is*** $\mu_z = a_0/(1+a)$***.***

Assumption 3: All stock returns, r_{it}, follow white noise processes and the white noise processes are independent of the macroeconomic variable, z, and other stocks' returns for all lags.

$$r_{it} = \varepsilon_{it}\text{, } \textbf{\textit{for i = 1, …, N,}}$$

$$E(\varepsilon_{it}) = E(\varepsilon_{it}\varepsilon_{jt-s}) = 0 \ \ \forall s \neq 0 \ \textbf{\textit{for i, j = 1,…, N,}}$$

$$E(\varepsilon_{it}\varepsilon_{jt}) = 0 \ \textbf{\textit{for i}} \neq \textbf{\textit{j, and}}$$

$$\operatorname{var}(r_{it}) = \operatorname{var}(\varepsilon_{it}) = \sigma_i^2\textbf{.}$$

Now consider a regression equation

$$r_{it} = c_{0i} + c_i z_{t-1} + e_{it}, \tag{18}$$

which is similar to regression equation (1). Since z is independent of any stock's return, the expected values of the estimate for c_i are zero for all i. However, suppose I nonetheless estimate c_{0i} and c_i at month t for stock i over the period from $t - T$ to $t - 1$, the *OLS* estimates of the intercept and the regression coefficient at time t for stock i is

$$\hat{c}_{it} = \frac{\sum_{j=1}^{T}\left(r_{it-j} - \bar{r}_{it-1}\right)\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2}\text{, and}$$

$$\hat{c}_{0it} = \bar{r}_{it-1} - \hat{c}_{it}\bar{z}_{t-2},$$

where bars above variables mean time-series average so that $\bar{r}_{it} = \frac{1}{T}\sum_{j=0}^{T-1} r_{it-j}$ and $\bar{z}_t = \frac{1}{T}\sum_{j=0}^{T-1} z_{t-j}$. Then the one-month-ahead predicted return with intercept for month t, denoted by $\hat{r}_{it}$, is

$$\hat{r}_{it} = \hat{c}_{0it} + \hat{c}_{it} z_{t-2} = \bar{r}_{it-1} - \hat{c}_{it}\bar{z}_{t-2} + \hat{c}_{it} z_{t-1} = \bar{r}_{it-1} + \hat{c}_{it}\left(z_{t-1} - \bar{z}_{t-2}\right), \tag{19}$$

and the one-month-ahead predicted return without intercept at month *t*, $\hat{r}_{it}^{\circ}$, is

$$\hat{r}_{t}^{\circ} = \hat{c}_{it} z_{t-1} = \hat{c}_{it} z_{t-1}. \tag{20}$$

The cross-sectional covariances between the one-month-ahead predicted returns and the cumulative returns over *m* months prior to *t*, defined in Definition 8 and denoted by $\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^m\right)$ if intercepts are included in predicting returns and $\overline{\mathrm{cov}}\left(\hat{r}_t^{\circ}, r_{t-}^m\right)$ if intercepts are excluded, are

$$\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^m\right) = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{r}_{it} - \overline{\hat{r}_t}\right)\left(r_{it-}^m - \overline{r_{t-}^m}\right), \text{ and}$$

$$\overline{\mathrm{cov}}\left(\hat{r}_t^{\circ}, r_{t-}^m\right) = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{r}_{it}^{\circ} - \overline{\hat{r}_t}\right)\left(r_{it-}^m - \overline{r_{t-}^m}\right),$$

where $r_{it-}^m = \sum_{j=1}^{m} r_{it-j}$, $\overline{\hat{r}_t} = \frac{1}{N}\sum_{i=1}^{N}\hat{r}_{it}$, $\overline{r_{t-}^m} = \frac{1}{N}\sum_{i=1}^{N} r_{it-}^m$, and *m* is the momentum portfolio formation period.

Now, let's consider expectations of the cross-sectional covariances, $E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right]$ and $E\left[\overline{\mathrm{cov}}\left(\hat{r}_t^{\circ}, r_{t-}^m\right)\right]$. As in Subsection IV.A, they can be written as

$$E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] = \frac{1}{N}\sum_{i=1}^{N} E\left(\hat{r}_{it} - \overline{\hat{r}_t}\right)\left(r_{it-}^m - \overline{r_{t-}^m}\right) = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{N-2}{N}E\left(\hat{r}_{it} r_{it-}^m\right) + \frac{1}{N^2}\sum_{k=1}^{N} E\left(\hat{r}_{kt} r_{kt-}^m\right)\right].$$

Since $\hat{r}_{it} = \bar{r}_{it-1} + \hat{c}_{it}\left(z_{t-1} - \bar{z}_{t-2}\right)$ in Equation (19), the above equation can be written as

$$E\left[\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] = \frac{1}{N}\sum_{i=1}^{N}\left[\begin{array}{l} \dfrac{N-2}{N} E\left\{\left[\bar{r}_{it-1} + \hat{c}_{it}\left(z_{t-1} - \bar{z}_{t-2}\right)\right]r_{it-}^m\right\} \\ + \dfrac{1}{N^2}\sum_{k=1}^{N} E\left\{\left[\bar{r}_{kt-1} + \hat{c}_{kt}\left(z_{t-1} - \bar{z}_{t-2}\right)\right]r_{kt-}^m\right\} \end{array}\right]. \tag{21}$$

Also, under Assumption 3,

$$E\left(\bar{r}_{it-1} r_{it-}^m\right) = 1/T \sum_{j=1}^{m} E\left(r_{it-j}^2\right) = \sigma_i^2\, m/T\,. \tag{22}$$

Under Assumptions 2 and 3, the following can be shown

$$E\left[\hat{c}_{it}\left(z_{t-1} - \bar{z}_{t-2}\right)r_{it-}^m\right] = E\left[\sum_{j=1}^{m} r_{it-j}\, \frac{\sum_{j=1}^{T}\left(r_{it-j} - \bar{r}_{it-1}\right)\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2}\left(z_{t-1} - \bar{z}_{t-2}\right)\right]$$

$$= \sigma_i^2 E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2}\left(z_{t-1} - \bar{z}_{t-2}\right)\right] - \frac{m\sigma_i^2}{T} E\left[\frac{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2}\left(z_{t-1} - \bar{z}_{t-2}\right)\right].$$

Since $\dfrac{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2} = 0$,

$$E\left[\hat{c}_{it}\left(z_{t-1} - \bar{z}_{t-2}\right)r_{it-}^m\right] = \sigma_i^2 E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2}\left(z_{t-1} - \bar{z}_{t-2}\right)\right]. \tag{23}$$

If I substitute $E\left(\bar{r}_{it-1} r_{it-}^m\right)$ and $E\left[\hat{c}_{it}\left(z_{t-1} - \bar{z}_{t-2}\right)r_{it-}^m\right]$ in Equation (21) with Equations (22) and (23), Equation (21) can be written as

$$E\left[\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] = \frac{1}{N}\sum_{i=1}^{N}\left\{\frac{N-2}{N}\left[E\left(C_t\right)\sigma_i^2\right] + \frac{1}{N^2}\sum_{k=1}^{N}\left[E\left(C_t\right)\sigma_k^2\right]\right\},$$

where

$$C_t \equiv \frac{m}{T} + \frac{\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2}\left(z_{t-1} - \bar{z}_{t-2}\right). \tag{24}$$

Finally, the expectation of the cross-sectional covariance can be written as

$$E\left[\overline{\operatorname{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] = E\left(C_t\right)\Sigma, \tag{25}$$

where $\Sigma \equiv (N-1)/N^2 \sum_{k=1}^{N} \sigma_k^2$, as in Equation (8).

In a similar manner, the expectation of the cross-sectional covariance between the predicted returns without intercepts and the previous cumulative m-month returns, $E\left[\overline{\operatorname{cov}}\left(\hat{r}_t^{\circ}, r_{t-}^m\right)\right]$, is

$$E\left[\overline{\operatorname{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] = E\left(D_t\right)\Sigma, \tag{26}$$

where

$$D_t \equiv \frac{\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_t\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_t\right)^2} z_{t-1}. \tag{27}$$

IV.C.2 Signs of expectation of the cross-sectional covariance between predicted returns and previous *m*-month returns using hypothetical macroeconomic variable

Since Σ is positive, the signs of the expected cross-sectional covariance between predicted returns and the cumulative m-month lagged returns in Equations (25) and (26) depend on $E(C_t)$ and $E(D_t)$. I will analytically determine the signs of $E(C_t)$ and $E(D_t)$ shortly. However, since C_t and D_t do not follow known probability distributions under Assumption 2, it is difficult to derive the expected values and variances of C_t and D_t. Therefore, I estimate the expected values and standard deviations of C_t and D_t using a *Monte Carlo* method for various a_0's and a's for m = 6 and T = 60. Before presenting the results from the *Monte Carlo* experiment, I briefly investigate the signs of the two quantities. First, the expected value of C_t is positive if the first order autoregressive coefficient for the hypothetical macroeconomic variable is positive and m is sufficiently smaller than T. To see the point, I can show that

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^{2}}\left(z_{t-1}-\bar{z}_{t-2}\right)\right]$$

$$=E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^{2}}\left(z_{t-1}-\bar{z}_{t-2}\right)\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right]\times\Pr\left(\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right)$$

$$+E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^{2}}\left(z_{t-1}-\bar{z}_{t-2}\right)\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]\times\Pr\left(\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right).$$

$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^{2}}\left(z_{t-1}-\bar{z}_{t-2}\right)\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right]>0$, and

$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^{2}}\left(z_{t-1}-\bar{z}_{t-2}\right)\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]>0$, if m is sufficiently smaller than T and z is positively autocorrelated, so,

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^{2}}\left(z_{t-1}-\bar{z}_{t-2}\right)\right]>0.$$

Therefore, $E(C_t)$ is positive since $C_t = \frac{m}{T} + \frac{\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2}\left(z_{t-1} - \bar{z}_{t-2}\right)$. This means that the expectation of the cross-sectional covariance between predicted returns with intercepts and the previous m-month returns is positive.

The expected value of D_t is also positive. First, suppose that the unconditional mean of the macroeconomic variable is positive, i.e. $\mu_z = a_0/(1-a) > 0$ in Assumption 2. Then, the expectation of D_t conditional on that $\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right) > 0$ is positive. In other words,

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2} z_{t-1} \,\middle|\, \sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right) > 0\right] > 0.$$

This can be shown as follows. If recent z values are higher than their average during the previous T periods from $t - T - 1$ to $t - 2$, i.e., if $1/m \sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right) > \bar{z}_{t-2}$, then z_{t-1} tends to be higher than the average value, $\bar{z}_{t-2}$, because I assume that the hypothetical macroeconomic variables are positively serially correlated. This implies that z_{t-1} tends to be positive, since unconditional expectation of $\bar{z}_{t-2}$ is positive. Therefore, the above equation holds true if μ_z is positive.

However the sign of the expectation of D_t conditional on $\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right) < 0$ when $\mu_z > 0$ depends on the magnitude of μ_z. If μ_z is high, then the conditional expectation,

$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]$, is negative. This is because if μ_z is high and $\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0$, z_{t-1} still tends to be positive since the unconditional expectation of $\bar{z}_{t-2}$ is high. In this case,

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right]$$

$$> abs\left\{E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]\right\},$$

as long as μ_z is positive, where abs() means absolute value. The above inequality implies $E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\right]>0$, if μ_z is high, since $\Pr\left(\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right)=\Pr\left(\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right)=0.5$.

If μ_z is low, then the conditional expectation, $E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]$, is positive because if μ_z is low and $\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0$, then z_{t-1} tends to be negative. This and the fact that

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right]$$ implies that

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\right]>0$$, if μ_z is low. Therefore

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\right]>0 \text{ if } \mu_z, > 0. \tag{28}$$

Second, let's assume that the long-term mean of the macroeconomic variable is negative.

Then

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]>0, \text{ and}$$

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]$$

$$> abs\left\{E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right]\right\}.$$

It follows that

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2} z_{t-1}\right]>0 \text{ if } \mu_z, < 0. \tag{29}$$

Finally, if $\mu_z = 0$, since

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2}z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)>0\right]>0\text{, and}$$

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2}z_{t-1}\middle|\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)<0\right]>0\text{,}$$

$$E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2}z_{t-1}\right]>0\ \text{ if } \mu_z\text{, } = 0. \tag{30}$$

From Inequalities (28), (29) and (30),

$$E(D_t)=E\left[\frac{\sum_{j=1}^{m}\left(z_{t-1-j}-\bar{z}_{t-2}\right)}{\sum_{j=1}^{T}\left(z_{t-1-j}-\bar{z}_{t-2}\right)^2}z_{t-1}\right]>0$$

and this implies that the expectation of the cross-sectional covariance between predicted returns without intercepts and the previous *m*-month returns are positive regardless of the unconditional expectation of the macroeconomic variables. Analyses in this subsection suggest that even one macroeconomic variable can appear to explain momentum profits if the macroeconomic variable is sufficiently persistent.

IV.C.3 A *Monte Carlo* experiment

Table 2.6 shows the results from a *Monte Carlo* experiment. I assume that the hypothetical macroeconomic variable follows a first order autoregressive process as specified in Assumption 2, i.e. $z_t = a_0 + az_{t-1} + \varepsilon_{zt}$, so the unconditional expectation of *z*, μ_z, is $a_0/(1\text{-}a)$. For each choice of *a* and μ_z, I simulate a time-series of the hypothetical macroeconomic variable, z, from t = -200 to t = 61 with $\sigma_{\varepsilon z}$ = 0.27, where $\sigma_{\varepsilon z} = \left[E\left(\varepsilon_{zt}^2\right)\right]^{1/2}$.

I assume that $\sigma_{\varepsilon z}$ = 0.27 because it is the average standard error of residuals when I estimate the four true macroeconomic variables as a first order autoregressive processes. I discard the first 201st z values from t = -200 to t = 0 in order to avoid potential bias from the initial values of the simulation. Then I calculate C and D using the remaining z values for m = 6 and T = 60. I repeat this procedures 10,000 times so I have 10,000 values of C and D for each pair of a and μ_z. Table 2.6 presents simulation means and standard deviations of the calculated values of C and D for a = 0.1, …, 0.9 and μ_z = 0, 1, 3, 5, 7, and 9.[12]

Simulation mean values of C are all positive regardless of a or μ_z as I showed in the previous subsection. Since $E\left[\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] = E(C_t)\Sigma$ in Equation (25), where Σ is positive, this implies that $E\left[\overline{\text{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] > 0$, where m = 6. Therefore, if the macroeconomic variable is positively serially correlated, the expected cross-sectional covariance between the past 6-month returns and one-month-ahead predicted returns with intercepts is positive. Further, this implies that the expected predicted momentum profit from the macroeconomic variable is positive, and finally the expected predicted-return-adjusted momentum profits are less than raw momentum profits even if the macroeconomic variable is independent of stock returns as long as the macroeconomic variable is positively serially correlated. Also, Table 2.6 suggests that the mean value of C is an increasing function of a, but independent of μ_z. Therefore, if I adjust momentum profits

[12] The reason that I do not use negative μ_z is that the probability distributions of C and D are the same if the absolute value of μ_z are the same regardless of whether it is positive or negative.

for predicted returns with intercepts, the adjusted momentum profits will be lower if I predict the stock returns using a more highly persistent macroeconomic variable. Finally, the simulation standard deviations of C appear to be constant across different long-term means of the macroeconomic variables.

Also, according to Table 2.6, the simulation mean values of D are mostly positive as suggested in the previous subsection. The simulation mean values of D are in general an increasing function of a with few exceptions. It is noticeable that the simulation standard deviations of D are monotonically increasing with a and μ_z for the range in Table 2.6, and more importantly, higher than the simulation standard deviations of C in general. For instance, when $a = 0.9$ and $\mu_z = 7$, the standard deviation of simulated D's is 1.36 while the standard deviation of simulated C's is only 0.12. Except for $\mu = 0$, the standard deviation of simulated D is much higher than that of simulated C. This suggests that if I adjusted momentum profits for predicted returns without intercepts, the absolute value of the t-value for the predicted-return-adjusted profits without intercepts would be lower than that with intercept. Therefore, if I predict returns without intercept, it is more likely that I will have insignificant predicted-return-adjusted momentum profits either with positive or negative sign, which is consistent with the results in Table 2.4.

These analyses along with the results in Table 2.1 where all of the macroeconomic variables are highly persistent suggest that the predictive power of the macroeconomic variables for momentum profits can come from a spurious relation between the predicted returns and returns during the momentum portfolio formation period.

IV.D. Adjustments in parameter estimation periods

I have shown that the explanatory power of the macroeconomic variables for momentum profits might come from a spurious relation between the one-month-ahead predicted returns and the momentum portfolio formation period returns induced when the macroeconomic variables are highly persistent and the momentum portfolio period is included in the parameter estimation period. However, excluding the momentum portfolio formation period from the parameter estimation period may not avoid this spurious relation completely because of persistence in the momentum profits in both the pre-formation and post-formation periods. CS show that even when momentum profits are measured over a six-month period with a six-month gap after the formation period, momentum profits are significantly positive. Also, they find that the monthly return differentials between winner and loser portfolios are significantly positive when returns are measured in a six-month period immediately prior to, or with a six-month gap prior to the momentum portfolio formation period. These facts suggest that even if I estimate the parameters in Equation (1) during the period before the momentum portfolio formation period or six months after formation period, predicted-return-adjusted momentum profits can be affected by the spurious relation if the macroeconomic variables are highly persistent.

For example, suppose that I construct a momentum portfolio at the beginning of month t based on the previous 6-month return over the period from t-6 and t-1 and estimate the parameters in Equation (1) over the period from t-66 to t-7. From the findings by CS, the winner portfolio constructed at month t tends to have performed better than the loser portfolio in six-month periods both *t*-12 through *t*-7 and *t*-18 through *t*-13. Therefore, the parameter estimation period, *t*-66 through *t*-7, includes the period from *t*-18 to *t*-7 in which the winner portfolio tends to performed better than the loser portfolio. Also, Table 2.1 shows that the macroeconomic variables are so persistent that the averages of the estimates of the autocorrelation coefficients for the four macroeconomic variables at lag 6 and 12 are 0.81 and 0.67, respectively. These two facts indicate that even though there is a 6-month gap between the parameter estimation period and the momentum portfolio formation period, the spurious relation between the one-month-ahead-predicted returns and stock returns over the period from *t*-18 to *t*-7 still can make the macroeconomic variables appear to predict the momentum profits. This implies that in order to measure the potential explanatory power of the macroeconomic variables for momentum profits in a way that is free from the spurious relation effect, I should exclude periods at least 12 months before and after the momentum portfolio formation period.

Under this adjustment of parameter estimation periods, there is no concern that the estimated intercepts may capture some of returns during the formation period, since the parameter estimation periods and formation periods are not overlapping any more. Therefore, there is no reason to exclude intercepts in predicting returns.[13] However, I also calculate predicted-return-adjusted momentum profits without intercepts for comparison purposes.

[13] If the difference in unconditional expected returns contributes to momentum profits significantly as Conrad and Kaul (1998) argue, there are still some concerns. However, Jegadeesh and Titman (2002) repute Conrad and Kaul's arguments and show that the difference in unconditional expected returns contributes little to the momentum profits, if any.

IV.D.1 Methodology

In this section, I adjust momentum profits for one-month-ahead predicted returns as CS do, but I estimate the parameters in Equation (1) using two different parameter estimation periods. For the first estimation period, when I construct momentum portfolio at the beginning of month t, I estimate parameters using 60 months of observations from $t-47$ to $t-19$ and from $t+12$ to $t+41$, and use the estimated parameters in calculating predicted returns during the holding period, which is from t to $t+5$, in order to eliminate possible spurious effects between predicted returns and momentum profits. I still use one-month lagged realizations of the macroeconomic variables to predict returns. Specifically, the weight vector for the momentum portfolio constructed at month t is $\dot{\mathbf{w}}_t = \begin{bmatrix}\dot{w}_{1t} & \cdots & \dot{w}_{Nt}\end{bmatrix}'(10/N)$, where $\dot{w}_{it} = 1$ if $i \in$ winner decile, $\dot{w}_{it} = -1$ if $i \in$ loser decile and $\dot{w}_{it} = 0$ otherwise. Let's denote the parameter vector estimated at month t for stock t using data from $t-47$ to $t-19$ and from $t+12$ to $t+41$ to be $\hat{\mathbf{c}}^1_{it}$, so $\hat{\mathbf{c}}^1_{it} = \begin{bmatrix}\hat{c}^1_{0it} & \hat{c}^1_{1it} & \hat{c}^1_{2it} & \hat{c}^1_{3it} & \hat{c}^1_{4it}\end{bmatrix}'$. Since the momentum strategy holds this position for the next six months, the weight vector of the momentum strategy at time t is $\mathbf{w}_t = 1/6\sum_{j=0}^{5}\dot{\mathbf{w}}_{t-j}$ as in Definition 1 and the predicted return on stock i for month t, denoted, $\hat{r}^1_{it}$, can be written as

$$\hat{r}^1_{it} = \frac{1}{6}\sum_{j=1}^{5}\mathbf{x}_{t-1}\hat{\mathbf{c}}^1_{it-j}\ , \tag{31}$$

where $\mathbf{x}_t = \begin{bmatrix}1 & DIV_t & TERM_t & YLD_t & DEF_t\end{bmatrix}$. This is because the parameters are estimated when the momentum portfolios are formed and fixed throughout the holding period. If I define $\hat{\mathbf{r}}_t^1$ to be a vector of the predicted returns in Equation (31) for month *t*, so $\hat{\mathbf{r}}_t^1 = \begin{bmatrix} \hat{r}_{1t}^1 & \cdots & \hat{r}_{Nt}^1 \end{bmatrix}$, the predicted momentum profit for month *t* under the first estimation period scheme, $\hat{\pi}_t^1$, can be written as

$$\hat{\pi}_t^1 = \mathbf{w}_t' \hat{\mathbf{r}}_t^1 ,$$

and the predicted-return-adjusted momentum profit for month *t*, denoted π_t^{a1}, can be written as

$$\pi_t^{a1} = \pi_t - \hat{\pi}_t^1 = \mathbf{w}_t' \left(\mathbf{r}_t - \hat{\mathbf{r}}_t^1 \right). \tag{32}$$

where π_t is the raw momentum profit for month *t* defined in Definition 2. Similarly, I can define the predicted-return-adjusted momentum profit without intercept under the first parameter estimation period scheme, denoted $\pi_t^{\circ a1}$, as follows

$$\pi_t^{\circ a1} = \pi_t - \hat{\pi}_t^{\circ 1} = \mathbf{w}_t' \left(\mathbf{r}_t - \hat{\mathbf{r}}_t^{\circ 1} \right), \tag{33}$$

where predicted returns exclude intercepts. In this case there is a 20.5-month backward gap and an 8.5-month forward gap on average between the parameter estimation period and the prediction period.

Under the second estimation period scheme, I estimate parameters using observations from *t* – 72 to *t* – 13 and use the estimated parameters to calculate predicted returns during the holding period, which is from *t* to *t* + 5. Let's denote predicted-return-adjusted momentum profit with intercepts for month *t* under the second estimation period scheme to be π_t^{a2}, then

$$\pi_t^{a2} = \pi_t - \hat{\pi}_t^2 , \tag{34}$$

where $\hat{\pi}_t^2$ is the predicted momentum profit with intercepts for month t under the second estimation period scheme. Similarly, predicted-return-adjusted momentum profits without intercepts for month t, denoted $\pi_t^{\circ a2}$, can be written as

$$\pi_t^{\circ a2} = \pi_t - \hat{\pi}_t^{\circ 2}, \tag{35}$$

where $\hat{\pi}_t^{\circ 2}$ is predicted momentum profit without intercepts for month t under the second estimation period scheme. In this case, there is a 14.5-month backward gap between parameter estimation period and the prediction period on average. If the predictive power of the macroeconomic variables documented by CS comes from the spurious relation between persistent macroeconomic variables and the momentum profits, then this methodological adjustment should eliminate the predictive power of the macroeconomic variables. However, if this adjustment completely eliminates the explanatory power of the macroeconomic variables for momentum, I may conclude either that the coefficients of Equation (1) are time-varying and the 9- to 15-month gap between parameter estimation period and return prediction prevents us from estimating the true parameters, or that the predictive power originally comes from the spurious relation.

IV.D.2 Results

Table 2.7 presents the time-series averages and *t*-statistics of the predicted-return-adjusted momentum profits using two different parameter estimation periods introduced in the previous subsection. In order to compare with the results of CS in their Table III, I include predicted-return-adjusted momentum profits when returns are predicted with Equation (1) including the January dummy. Since I include stocks that have at least 24 months of observations when estimating the parameters, the sample periods and stocks included in the momentum portfolios for each month under the first and second estimation period schemes are different. For comparison purposes, I also include raw momentum profits for the subsample of stock-months used in each parameter estimation scheme. As Panel C shows, the raw momentum profits for these subsamples of stocks and months used in the two different parameter estimation period schemes are significantly positive for all sample periods. This implies that elimination of stocks that do not meet the 24-month observation requirement for estimating parameters does not affect the momentum phenomenon.

According to Panels A and B of Table 2.7, the predicted-return-adjusted momentum profits with intercepts for both parameter estimation periods are all significantly positive and similar to the raw momentum profits regardless of whether I include or exclude the January dummy in equation (1) for all sample periods. These suggest that if the parameter estimation period is not associated with time horizons during which momentum phenomena are documented, predicted returns with intercepts do not have predictive power for momentum profits.

However, if I exclude intercepts for predicted returns, I may not draw such a general conclusion. For instance, in Panel A and under the first parameter estimation scheme, the predicted-return-adjusted momentum profits are significantly negative over the sample period from January 1951 to December 1994, while they are significantly positive under the second parameter estimation scheme over the period from June 1954 to December

1994. Also, under the first parameter estimation scheme, predicted-return-adjusted momentum profits are positive but insignificant over the sample period from January 1951 to June 1963, but they are significantly negative over the sample period from July 1963 to December 1994. Under the second parameter estimation scheme, the predicted-return-adjusted momentum profits are significant for both subsamples, 6/54-6/63 and 7/63-12/94, but have different signs. This inconsistency is the same when I include the January dummy in Equation (1). These results suggest that the predicted returns without intercept estimates do not predict consistently the momentum profits if the parameter estimation periods are not associated with the periods during which the momentum phenomena are documented.

From the fact that momentum profits adjusted for predicted returns with intercept are significantly positive over the all sample periods with and without January dummy, I may conclude either that the parameters in Equation (1) are so time-sensitive that a 9- to 15-month gap prevents us from estimating the true parameters, or that the predictive power of the macroeconomic variables originally came from a spurious relation between the one-month-ahead predicted returns and the stock returns during the momentum formation period as I showed in previous section.

IV.E. Spurious explanatory power of random macroeconomic variables

If the explanatory power of the macroeconomic variables for momentum profits comes from a spurious relation between the persistent macroeconomic variables and stock returns during momentum portfolio formation, it naturally follows that any random variables that exhibit similar autocorrelations to the macroeconomic variables should appear to explain momentum profits. In this subsection, I generate random macroeconomic variables that have similar characteristics to the true macroeconomic variables and test whether the random variables appear explain the momentum profits as CS show with the true macroeconomic variables.

IV.E.1 Methodology

First, I estimate the following first-order autoregressive equation with time trend for each of the macroeconomic variables:

$$z_t = a_0 + b \cdot t + v_t \text{, and} \qquad (36)$$
$$v_t = a v_{t-1} + \varepsilon_t \text{.}$$

Table 2.8 presents maximum likelihood estimators of a_0, b, a, and standard deviations of residuals for *DIV*, *TERM*, *YLD*, and *DEF* over the period from January 1951 to December 1994. Next, I generate four of random variables that follow the estimated autoregressive processes for t = -100 through t = 528 and discard the first 101 values in order to avoid potential bias for initial values. Then, I calculate momentum profits adjusted for returns predicted by these random variables with and without intercepts as in Definitions 3 and 3′. I generate ten sets of the random variables and repeat these procedures 10 times.

IV.E.2 Results

Table 2.9 shows time-series averages and t-statistics of momentum profits adjusted for each set of the random macroeconomic variables over the three different sample periods.

Also the grand average, maximum and minimum values of the monthly predicted-return-adjusted momentum profits and *t*-statistics are presented over the 10 simulations. For the entire sample period, from January 1953 to December 1994, the grand average of the monthly predicted-return-adjusted momentum profits is -4.62 percent (maximum: -4.11 percent, minimum: -4.94 percent) and average *t*-statistic is -17.13 (maximum: -15.23, minimum: -18.22) when I include intercepts in predicting returns, while the monthly momentum profit adjusted for returns predicted by the true macroeconomic variables with intercept is -4.81 percent with *t*-statistic of -16.97 as in Table 2.4. The monthly momentum profits controlled by the true macroeconomic variables and their *t*-statistic are very close to the grand average of those from the 10 simulations and none of the predicted-return-adjusted momentum profits from the 10 simulations is significantly different from those from the true macroeconomic variables. This is true for both subsample periods, 1/53-6/63 and 7/63-12/94. These results imply that all of the 10 sets of simulated random variables appear to completely explain momentum profits just as do the true macroeconomic variables when I include intercepts in predicting returns, which is consistent with my argument that explanatory power of the macroeconomic variables may comes from spurious relation between the one-month-ahead predicted returns and stock returns during momentum portfolio formation period.

Also, when I exclude intercepts for predicting returns, all simulated random macroeconomic variables appear to explain momentum profits over the entire sample period. The maximum *t*-value is 1.58 for the 6th simulation, in which I would still conclude that adjusted momentum profits are not significantly positive at the 90 percent confidence level. Other than this case, all of the simulated random macroeconomic variables produce significantly or insignificantly negative predicted-return-adjusted momentum profits. So, all of the simulated random variables appear to explain momentum profits even when I exclude the intercepts for predicted returns. It was well expected that the ranges of adjusted momentum profits and *t*-values are larger in the random simulations when I exclude the intercepts than when I include them. For two sub-sample periods, I have similar results except for two cases. In the first simulation, the adjusted momentum profit is 7.16 percent, and it is significantly positive over the subsample period from January 1953 to June 1963 and in the 6th simulation, the adjusted momentum profit is 2.85 percent and the *t*-value is 2.57 over the subsample period from July 1963 to December 1994. In sum, all of the 10 simulations appear to explain momentum profits when I include intercepts in predicting returns over all of the three sample periods. If I exclude intercepts in predicting returns, all of the 10 simulations also appear to explain momentum profits over the entire sample period, and only one simulation fails to explain the momentum profits for each subsample period.

From the findings in this subsection, along with those in Subsection IV. D, I may conclude that the seemingly predictive power of the macroeconomic variables for momentum profits comes from a spurious relation between the one-month-ahead predicted returns and stock returns during momentum portfolio formation period due to high persistence in the macroeconomic variables.

IV.F. Predicted versus raw returns

As described in Subsection II.B.2, CS show that a six-month/six-month momentum strategy based on returns predicted by the macroeconomic variables (in Definition 5) produces significantly positive profits. Also, CS find that the past predicted returns have additional predictive power for future returns even within quintiles that are first sorted based on past raw returns, while raw returns do not have additional predictive power for future returns once controlled by the predicted returns as introduced in Subsection II.B.3. CS argue that this is sufficient counter evidence to a conjecture that predicted returns are simply capturing information contained in past returns and argue that the past raw returns are capturing information contained in the predicted returns by the macroeconomic variables as "*the ability of past raw returns to predict future returns is due to information contained in the predicted component of returns*."[14] I do not believe this is the only interpretation of CS' findings described in the previous paragraph. I have shown that the one-month-ahead predicted returns from the macroeconomic variables are spuriously correlated to past six-month raw returns. Jegadeesh and Titman (1993) show that a nine-month/six-month or twelve-month/six-month momentum strategy produces higher profits than a six-month/six-month momentum strategy. Therefore, if the returns predicted by the macroeconomic variables are more strongly correlated to longer-period past returns, such as previous nine-month or 12-month returns, than the previous six-month returns, then sorting stocks by past predicted returns can generate additional return differentials even once controlled for the past 6-month returns. In order to show my argument, in Subsection IV.F.2, I will show that the returns predicted by the macroeconomic variables

[14] Page 1003 in Chordia and Shivakumar (2002).

are more strongly correlated to longer-period past raw returns than past six-month raw returns under Assumption 1 that all stock returns follow white noise processes and the macroeconomic variables are independent of all stock returns for all lags. This correlation is spurious since I assumed that the macroeconomic variables are independent of stock returns. Also, if the additional predictive power of the past predicted returns within quintiles that are sorted based on previous six-month raw returns is due to stronger spurious correlation between the predicted returns and longer-period past raw returns than six-month past returns, then simply lengthening the portfolio formation period should eliminate the additional predictive power of the predicted returns. I will directly test this argument in Subsection IV.F.2. Specifically, I find that when I lengthen the portfolio formation period to 9 to 12 months, the additional predictive power of the predicted returns disappears.

In addition to my spurious correlation argument, Cooper, Gutierrez, and Hameed (2004) show that when they exclude stocks priced under $1 from the portfolios or skip the last month between the portfolio formation period and the holding period, the additional return differentials among portfolios formed based on predicted return disappear. I will briefly explain this phenomenon in Subsection IV.F.2. Before presenting my arguments and the results from the lengthened formation period, I replicate Table VII of CS with the macroeconomic variables that I have in order to see whether my findings are different from CS' simply because the macroeconomic variables that I have are different from CS'.

IV.F.1 Replication of CS tests with my macroeconomic variables

Table 2.10 compares CS' Table VII and my results. In this case, the portfolios are formed based on the previous cumulative six-month raw returns or predicted returns and are held for the next six months as described in Subsection II.B.3.[15] For explanation purposes, I denote matrix **RP** to be a 5 × 5 matrix, whose (i, j)th elements, RP_{ij}, represents the time-series average return on the portfolio that is the ith quintile sorted based on the previous 6-month predicted returns within the jth quintile that was first sorted based on the previous 6-month raw returns, where 5th quintile means the portfolio that has highest previous raw or predicted returns. Also, I denote matrix **PR** to be a 5 × 5 matrix, whose (i, j)th elements, PR_{ij}, represents the time-series average return on the portfolio that is in the jth quintile sorted based on previous 6-month raw returns within the ith quintile that was first sorted based on previous cumulative predicted returns.

As shown in Table 2.10, CS find that $(RP_{5j} - RP_{1j})$ is significantly positive for j = 2, 3, 4, and 5. t-statistics are 3.17, 3.57, 3.46, and 3.46 for j = 2, 3, 4, and 5, respectively. These suggest that within the 2nd, 3rd, 4th, and 5th quintiles that are first sorted by previous raw returns, the previous six-month predicted returns have additional predictive power for future returns. This is the same with my macroeconomic variables. The t-statistics of $(RP_{5j} - RP_{1j})$ from my macroeconomic variables are 3.67, 3.75, 3.69, and 4.20 for j = 2, 3, 4, and 5, respectively.[16] My macroeconomic variables seem to have higher predictive power for future returns than CS', since all t-statistics are higher than those from CS'

[15] For this test, CS include the intercept estimates for predicting returns.
[16] $(RP_{51} - RP_{11})$ is insignificant for both CS' and my macroeconomic variables.

macroeconomic variables. In contrast, CS show that ($PR_{i5} - PR_{i5}$) is insignificant for i = 1, 2, 3, and 4. t-statistics are 0.45, 1.06, 0.71 and 1.44 for i = 1, 2, 3, and 4, respectively. These suggest that raw returns do not have additional predictive power for future returns within the 1st, 2nd, 3rd, and 4th quintiles that are first sorted by previous predicted returns. This is exactly the same case as for my macroeconomic variables. The t-statistics of ($PR_{i5} - PR_{i5}$) are 0.79, 1.06, 0.99, and 1.42 for i = 1, 2, 3, and 4, respectively.[17] From the above results, CS conclude that the returns predicted by the macroeconomic variables are not simply capturing the effect of past returns, but 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. Comparisons of CS' and my results in Table 2.10 suggest that if CS used the macroeconomic variables that I have, they would draw the exactly same conclusions. Therefore, if I find different results from lengthening portfolio formation period, it is unlikely that the difference comes from difference in macroeconomic variables between CS' and ours.

IV.F.2 Cross-sectional correlation between predicted returns and past raw returns

Before presenting the results from lengthening the momentum portfolio formation period to 9 months or 12 months, let's consider the cross-sectional correlation between the one-month-ahead predicted returns and the previous m-month returns, defined as

[17] ($PR_{55} - PR_{15}$) is significantly positive for both CS' and my macroeconomic variables.

Definition 9: "Cross-sectional correlation coefficient between one-month-ahead predicted returns and the previous m-month returns, $\overline{\rho}_m$***, (shortly correlation coefficient between the predicted returns and the previous m-month returns)":***

$$\overline{\rho}_m \equiv \frac{E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right]}{\left\{E\left[\overline{\mathrm{var}}\left(\hat{r}_t\right)\right]\right\}^{1/2}\left\{E\left[\overline{\mathrm{var}}\left(r_{t-}^m\right)\right]\right\}^{1/2}},$$

where $\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^m\right) = 1/N\sum_{k=1}^{N}\left(\hat{r}_{kt} - \overline{\hat{r}}_t\right)\left(r_{kt-}^m - \overline{r_{t-}^m}\right)$ ***as in Definition 8,*** $\hat{r}_{it}$ ***is defined in Equation (3),*** $\overline{\hat{r}}_t$ ***,*** r_{it-}^m***, and*** $\overline{r_{t-}^m}$ ***are defined in Definition 8, and where***

$\overline{\mathrm{var}}\left(\hat{r}_t\right) = 1/N\sum_{k=1}^{N}\left(\hat{r}_{kt} - \overline{\hat{r}}_t\right)^2$ ***, and*** $\overline{\mathrm{var}}\left(r_{t-}^m\right) = 1/N\sum_{k=1}^{N}\left(r_{kt-}^m - \overline{r_{t-}^m}\right)^2$ ***.***

The correlation coefficient between the predicted returns and the previous *m*-month returns measures the relative extent to which the predicted returns and previous *m*-month returns are correlated to each other, and is a better measure to compare relative associations of different-period lagged returns with the predicted returns than expected cross-sectional covariance. Suppose, for instance, that $E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^9\right)\right] > E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^6\right)\right]$. This means the cross-sectional covariance between the predicted returns and the previous nine-month returns is larger than the covariance between the predicted returns and previous six-month returns on average. However, because the cumulative nine-month returns have higher variance than the cumulative six-month returns in general, $E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^9\right)\right] > E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^6\right)\right]$ does not tell whether it is because the association between the predicted returns and nine-month lagged returns is stronger than that between the predicted returns and six-month lagged returns or because the expected cross-sectional variance of nine-month lagged returns is higher than that of six-month lagged returns. However, if $\overline{\rho}_9 > \overline{\rho}_6$, then I can tell that the predicted returns are more strongly associated with nine-month lagged returns than six-month lagged returns.

Now, suppose again that stock returns follow white noise processes and are independent of the macroeconomic variables as in Assumption 1. Then

$$E\left[\overline{\mathrm{var}}\left(r_{t-}^{m}\right)\right] = \frac{1}{N}\sum_{k=1}^{N} E\left(rk_{it-}^{m} - \overline{r_{t-}^{m}}\right)^2 = \frac{1}{N}\sum_{k=1}^{N} E\left[\left(r_{kt-}^{m}\right)^2 - 2r_{kt-}^{m}\overline{r_{t-}^{m}} + \left(\overline{r_{t-}^{m}}\right)^2\right]$$

$$= \frac{1}{N}\sum_{i=1}^{N}\left(m\sigma_k^2 - \frac{2m}{N}\sigma_k^2 + \frac{1}{N^2}\sum_{k=1}^{N} m\sigma_k^2\right) = m\frac{N-1}{N^2}\sum_{k=1}^{N}\sigma_k^2 .$$

So,

$$E\left[\overline{\mathrm{var}}\left(r_{t-}^{m}\right)\right] = m\Sigma , \tag{37}$$

where $\Sigma \equiv (N-1)/N^2 \sum_{k=1}^{N}\sigma_k^2$ as in Equation (8). From Equation (8), it can be shown that

$$E\left[\overline{\mathrm{cov}}\left(\hat{r}_t , r_{t-}^{m}\right)\right] = E\left[A_t(m)\right]\Sigma , \tag{38}$$

where

$$A_t(m) \equiv \mathbf{x}_{t-1}\left(\mathbf{X}'_{t-2}\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}'_{t-2}\boldsymbol{\iota}_m^{*} ,$$

where $\mathbf{x}_{t-1}$, $\mathbf{X}_{t-2}$, and $\boldsymbol{\iota}_m^{*}$ are defined in Subsection IV. A. Using Equations (37) and (38)

$$\overline{\rho}_m = \frac{E\left[A_t(m)\right]\Sigma^{1/2}}{m^{1/2}\left\{E\left[\overline{\mathrm{var}}\left(\hat{r}_t\right)\right]\right\}^{1/2}} .$$

Finally if I assume that $A_t(m)$ is a covariance stationary process for all m < 60 and that the unconditional expectation of $\overline{\text{var}}(\hat{r}_t)$ exists and denote Γ to be $\Sigma^{1/2} / \left\{E\left[\overline{\text{var}}(\hat{r}_t)\right]\right\}^{1/2}$, then

$$\bar{\rho}_m = \frac{E[A(m)]}{m^{1/2}}\Gamma, \tag{39}$$

where Γ is a positive number that is independent of *m*.

Table 2.11 presents the time-series average of $A_t(m)/m^{1/2}$ for the range of *m* from 3 to 16 months using the macroeconomic variables. Under the assumption that $A_t(m)$ is a covariance stationary process, the time-series average of $A_t(m)/m^{1/2}$ is an unbiased estimator of $E[A(m)]/m^{1/2}$ and under Assumption 1, the cross-sectional correlation coefficient between the one-month-ahead predicted return from the macroeconomic variables and previous *m*-month returns, defined in Definition 9, is proportional to $E[A(m)]/m^{1/2}$. According to Table 2.11, the cross-sectional correlation coefficient is strongest when $m = 9$. Therefore, momentum portfolios based on past cumulative predicted returns over the past 6-months are more strongly correlated with longer-period returns than just past 6-month returns. This fact along with findings of Jegadeesh and Titman (1993) may explain CS' findings in two-way sorted portfolios that predicted returns appear to have additional predictive power for future returns even once stocks are controlled for their past raw return. Since predicted returns are more strongly correlated with longer-period lagged returns than six months and a nine-month/six-month or twelve-month/six-month momentum strategy produces more profits than the six-month/six-month momentum strategy, $RP_{5j} - RP_{1j}$ can be positive in CS' tests even if the predictive power of the predicted returns originally comes from a spurious relation between the persistent macroeconomic variables and stock returns during the momentum portfolio formation period. This argument suggests that if I lengthen the portfolio formation period to nine or twelve months, $RP_{5j} - RP_{1j}$ in Subsection IV.F.1 should not be significantly positive. In next section, I replicate CS' test introduced in IV.F.1 except for portfolio formation period.

Before, presenting the results, let's investigate why skipping the last month between the portfolio formation period and the holding period or \$1 price screening eliminates the additional predictive power of the predicted return as shown by Cooper, Gutierrez, and Hameed (2004). Jegadeesh and Titman (1993) show that the momentum strategies that have a one-week lag between the formation period and the holding period generate higher profits than those without a one-week lag. Jegadeesh (1990) also shows that one-month stock returns exhibit strong reversals, which might be due to market microstructure effects or investors' overreaction in short-term horizons. No matter what are the reasons for the short-term return reversals, these findings suggest that momentum strategies with a one-month lag between the formation period and holding period might have smaller short-term reversal effects. Momentum strategies based on the predicted returns does effectively exclude raw returns from the last month of the formation period.

In order to see the point, let's consider the six-month/six-month momentum strategy based on predicted returns defined in Definition 5. I defined the weight vector of the momentum portfolio at month t as follows

$$\mathbf{w}_t^p = \sum_{j=0}^{5} \dot{\mathbf{w}}_{t-j}^p \left(\frac{1}{6}\right), \tag{40}$$

where $\dot{\mathbf{w}}_t^p$ is a weight vector of the momentum portfolio constructed at month t, so $\dot{\mathbf{w}}_t^p = \begin{bmatrix} \dot{w}_{1t}^p & \cdots & \dot{w}_{Nt}^p \end{bmatrix}(10/N)$, where $\dot{w}_{it}^p = 1$ if stock i's cumulative six-month one-month-ahead predicted return belongs to the top ten percent, $\dot{w}_{it}^p = -1$ if stock i's cumulative six-month predicted return belongs to the bottom ten percent and $\dot{w}_{it}^p = 0$ otherwise. The weight vector of the momentum portfolio held at the beginning of month t, $\mathbf{w}_t^p$, in Equation (40) does not reflect stock returns for month $t - 1$. Even for $j = 0$ in Equation (40), $\dot{\mathbf{w}}_t^p$ reflects $\hat{r}_{it-1}$, $\hat{r}_{it-2}$, …, $\hat{r}_{it-6}$, for $i = 1, \ldots, N$, where $\hat{r}_{it}$ is the one-month-ahead predicted return from the Equation (1). Also, the parameters in Equation (1) are estimated with the realizations of the macroeconomic variables from $t - 62$ to $t - 3$ and realizations of stock i's returns from $t - 61$ to $t - 2$ and $\hat{r}_{it-1}$ is calculated with the realizations of the macroeconomic variables at month $t - 2$ and the estimated parameters. So, even the most recently constructed momentum portfolio does not reflect realizations of stock returns for month $t - 1$. Since $\mathbf{w}_t^p$ does not reflect the last month's stock returns, the momentum strategy based on predicted returns effectively skips the last month between the formation period and holding period. If there is a one-month gap between the formation period and holding periods as in Cooper, Gutierrez, and Hameed's (2004) counter test, portfolios formed at month t based on predicted returns do not reflect stock returns for month $t-1$ and $t-2$, while portfolios based on raw returns do not reflect stock returns for only month $t-1$. Also stocks priced under $1 are known to be subject to short-term return reversals probably because they tend to be highly illiquid. Therefore, when Cooper, Gutierrez, and Hameed (2004) exclude stocks priced under $1, the ability of portfolios formed based on the predicted returns within quintiles that are first classified by the past raw returns to produce additional return differentials can be significantly reduced. These might explain the appearance of the additional predictive power of the predicted returns from macroeconomic variables shown by CS and the disappearance of such additional predictive power when Cooper, Gutierrez, and Hameed (2004) skip one-month between the formation period and the holding period or exclude penny stocks from the portfolios. This explanation is still consistent with my argument that the predicted power of the macroeconomic variables comes from a spurious relation.

IV.F.3 12-month portfolio formation period

In Tables 2.12 and 2.13, I replicate Table 2.10 except for the portfolio formation periods. In Table 2.12, portfolios are formed based on the previous 12-month cumulative raw returns and predicted returns, and in Table 2.13, the portfolio formation period is 9 months. In both cases, the portfolio holding periods are 6 months as in Table 2.10. I do not skip one month between the formation period and holding period or exclude penny stocks from the portfolios. If the predicted returns from the macroeconomic variables contain real information for future stock returns and raw returns just capture the information contained in the predicted returns as CS argue, these methodological adjustments shouldn't affect the results in Table 2.10. However, if the appearance of the additional predictive power of the predicted returns due to spurious correlation between the predicted returns and longer-period past raw returns than six months as I argue, then lengthening the portfolio formation periods to 9 to 12 months should eliminate the additional differentials in returns among portfolios constructed based on the past predicted returns.

In contrast to the results in Table 2.10, $(RP_{5j} - RP_{1j})$ is insignificant for all j's in Panel A Table 2.12 and $(RP_{5j} - RP_{1j})$ is significantly positive only for $j = 2$ in Panel A of Table 2.13. These suggest that the past cumulative 12-month (and 9-month) predicted returns do not have additional predictive power for future returns once controlled by past 12-month (and 9-month) raw returns. However, in Panel B of Table 2.12, where stocks are first sorted by their past 12-month cumulative predicted returns and then sorted by past 12-month raw returns, $(PR_{i5} - PR_{i5})$ is significantly positive for all i's.[18] Also, in Panel B of Table 2.13, $(PR_{i5} - PR_{i5})$ is significantly positive at the 95 percent confidence level for all i's. These suggest that past 12-month (9-month) raw returns have additional predictive power even after controlled by past 12-month (9-month) predicted returns. Findings in Tables 2.12 and 2.13 suggest that past 12-month (9-month) raw returns have higher predictive power for future returns than past 12-month (9-month) predicted returns from the macroeconomic variables. These findings are consistent with my argument that the

[18] $(PR_{i5} - PR_{i5})$ is significantly positive at 95 percent confidence level for $i = 2$, 3, 4, and 5, and significantly positive at 90 percent confidence level for $i = 1$.

predicted returns are more strongly correlated to longer-period past returns than six-month returns.

V. Conclusions and Implications for Future Research

Since Jegadeesh and Titman (1993) first document that the intermediate-term momentum strategies produce positive profits, a number of researchers have tried to identify risk factors associated with the trading strategies. For an intermediate-horizon, there might be enough time for the systematic risk of stocks and, therefore, expected returns to change. Such time-varying expected returns can be reflected in the realizations during the immediate previous period, therefore momentum trading strategies can consistently produce positive profits. Even though this scenario is very plausible in theory, it is not easy to identify the time-varying systematic risk factors. I conclude that the appearance of business cycle model suggested by Chordia and Shivakumar (2002) to explain the momentum profits is likely to come from spurious relation between the highly persistent macroeconomic variables and already documented return continuation of stocks.

However, I do not know the degree to which Chordia and Shivakumar (2002)'s results suffer from the spurious relation. It might be true that all of the predictive power of the macroeconomic variables for momentum comes from the spurious relation, but it might be also true that half of the predictive power comes from the spurious relation. One potential extension of this study can be to estimate the residual predictive power after controlling for the spurious relation.

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Appendix 1

Table 2.1 Summary Statistics of the Macroeconomic Variables

Means, standard deviations and estimates of autocorrelation coefficients of the four macroeconomic variables over the period from January 1951 to December 1994 are reported in Panel A. *DIV* is the total dividend payments according to the CRSP value-weighted index over the previous twelve months divided by the current level of the index. *TERM* is the average yield of Treasury bonds with greater than 10 years to maturity minus the yield of T-bills that mature in 3 months. *YLS* is the yield of a T-bill that matures in 3 months. *DEF* is the average yield of bonds rated by Moody's Baa minus the average yield of bonds rated by Moody's Aaa.

Panel B presents estimates of contemporaneous correlations between the macroeconomic variables. Numbers in parentheses represent *p* values under the null that two macroeconomic variables are not correlated.

Panel A: Autocorrelations

	Mean	Std. Dev.	1	2	3	4	5	6	12	24	36	48	60
DIV	3.74	0.88	0.97	0.95	0.92	0.89	0.86	0.83	0.67	0.49	0.37	0.28	0.15
TERM	1.09	1.29	0.96	0.90	0.84	0.79	0.75	0.71	0.55	0.22	0.02	0.09	0.14
YLD	5.13	2.84	0.99	0.96	0.94	0.93	0.91	0.89	0.81	0.63	0.52	0.45	0.41
DEF	0.88	0.39	0.97	0.93	0.90	0.87	0.85	0.81	0.66	0.46	0.32	0.37	0.37

Panel B: Contemporaneous correlations

	TERM	*YLD*	*DEF*
DIV	-0.21	0.14	0.22
	(< 0.01%)	(0.11%)	(< 0.01%)
TERM		-0.36	0.09
		(< 0.01%)	(3.66%)
YLD			0.65
			(< 0.01%)

Table 2.2 Momentum Strategy Profits Adjusted for Predicted Returns from the Macroeconomic Variables (Comparison with CS)

Momentum portfolios are constructed as in Definition 1 (based previous six-month cumulative raw returns) for all Panels A, B, and C using all NYSE-AMEX stocks on the monthly CRSP table. Panel B shows the strategy's holding period monthly profits after adjusting for returns predicted by the business cycle model (Equation 1), defined by Definition 3′. Panel C shows the strategy's holding period monthly profits after adjusting for returns predicted by the business cycle model including January dummy. In other words, in Panel C, $r_{it} = c_{0i} + \sum_{k=1}^{4} c_{ik} z_{kt-1} + \theta \cdot Jandum + e_{it}$ is used to predict returns instead of Equation (1). For both Panels B and C, adjusted returns are measured as the intercept estimates plus residuals. The model parameters are estimated using data from time *t*-1 through *t*-60. A minimum of two years data is required for estimating the parameters. Panel A of this table presents the raw profits defined in Equation (2) from the momentum strategy for the subsample of stock-months used in Panels B and C. *t*-statistics are reported in parentheses. Numbers without parentheses are in percentage terms. The column titled "CS" gives the results in Table III of Chordia and Shivakumar (2002) and the column titled "Park" presents the my results using dataset provided by Pontiff.

	Non-Jan P10 – P1		Jan P10 – P1		Overall P10 – P1	
	CS	Park	CS	Park	CS	Park
			Panel A: Raw Profits			
1/53-12/94	1.39	1.43	-7.27	-7.19	0.69	0.71
	(7.60)	(7.94)	(-4.83)	(-4.74)	(2.95)	(3.04)
1/53-6/63	1.39	1.42	-4.83	-4.43	0.90	0.91
	(5.86)	(5.97)	(-3.36)	(-3.30)	(3.11)	(3.19)
7/63-12/94	1.39	1.43	-8.06	-8.17	0.62	0.64
	(6.03)	(6.32)	(-4.18)	(-4.12)	(2.10)	(2.17)
			Panel B: Adjusted Profits-Business Cycle Model Excludes January Dummy			
1/53-12/94	-0.67	-0.27	-16.30	-16.01	-1.94	-1.58
	(-0.47)	(-0.19)	(-3.46)	(-3.40)	(-1.41)	(-1.13)
1/53-6/63	-2.65	-1.62	-15.76	-13.32	-3.70	-2.64
	(-1.13)	(-0.65)	(-1.80)	(-1.56)	(-1.62)	(-1.1)
7/63-12/94	-0.01	0.17	-16.47	-16.96	-1.36	-1.23
	(-0.01)	(0.10)	(-2.29)	(-2.99)	(-0.81)	(-0.73)
			Panel C: Adjusted Profits-Business Cycle Model Includes January Dummy			
1/53-12/94	-1.01	-0.52	-13.31	-12.70	-2.02	-1.54
	(-0.71)	(-0.36)	(-2.95)	(-2.81)	(-1.47)	(-1.11)
1/53-6/63	-1.76	-0.70	-12.61	-9.78	-2.62	-1.49
	(-0.79)	(-0.3)	(-1.56)	(-1.22)	(-1.23)	(-0.66)
7/63-12/94	-0.77	-0.46	-13.53	-13.73	-1.81	-1.55
	(-0.44)	(-0.26)	(-2.49)	(-2.50)	(-1.08)	(-0.92)

Table 2.3 Time-series Averages and *t*-statistics of A_t, B_t, and X_t

For each month *t*, I calculate A_t, B_t, and X_t over the sample period from 1/53 to 12/94. $\mathrm{A}_t \equiv 1/6\sum_{j=0}^{5}\left[\mathbf{x}_{t-1}\left(\mathbf{X}'_{t-2}\mathbf{X}_{t-2}\right)^{-1}\mathbf{X}'_{t-2}\iota^{*}_{6,j}\right]$, where $\mathbf{x}_t$ is a vector of $\left[1 \quad DIV_t \quad TERM_t \quad YLD_t \quad DEF_t\right]$, $\mathbf{X}_t$ is a 60 × 5 matrix consisting the time-series of $\mathbf{x}_t$ from *t*-59 to *t*, and $\boldsymbol{\iota}^{*}_{6,j}$ is a 60 × 1 vector whose first (54-*j*) elements are zero, whose next *m* elements are ones and whose remaining elements are zeros. I show that conditional expectation of predicted momentum profit with intercept (defined in Definition 2) for month *t* on the realizations of the macroeconomic variables up to month *t*-1 is proportional to A_t under Assumption 1 in Equation (9) $\mathrm{B}_t \equiv 1/6\sum_{j=0}^{5}\mathbf{z}_{t-1}\left[\mathbf{Z}'_{t-2}\left(\mathbf{I}-\frac{\mathbf{u}'}{T}\right)\mathbf{Z}_{t-2}\right]^{-1}\mathbf{Z}'_{t-2}\left(\mathbf{I}-\frac{\mathbf{u}'}{T}\right)\boldsymbol{\iota}^{*}_{6,j}$, where $\mathbf{z}_t$ is a vector of $\left[DIV_t \quad TERM_t \quad YLD_t \quad DEF_t\right]$, $\mathbf{Z}_t$ is a 60 × 4 matrix consisting the time-series of $\mathbf{z}_t$ from *t*-59 to *t*. I show that conditional expectation of predicted momentum profit without intercept (defined in Definition 2′) for month *t* on the realizations of the macroeconomic variables up to month *t*-1 is proportional to B_t. Finally, $\mathrm{X}_t = 1/6\sum_{j=0}^{5}\boldsymbol{\iota}'\left[\mathbf{I}-\mathbf{Z}_{t-2}\left(\mathbf{Z}'_{t-2}\mathbf{Z}_{t-2}\right)^{-1}\mathbf{Z}'_{t-2}\right]^{-1}\boldsymbol{\iota}'\left[\mathbf{I}-\mathbf{Z}_{t-2}\left(\mathbf{Z}'_{t-2}\mathbf{Z}_{t-2}\right)^{-1}\mathbf{Z}'_{t-2}\right]\boldsymbol{\iota}^{*}_{6,j} = \mathrm{A}_t - \mathrm{B}_t$. I also show that conditional expectation of the difference between predicted momentum profits with and without intercepts is proportional to X_t. First row presents the time-series averages and *t*-statistics of A_t, B_t, and X_t over the entire sample period. I also report the time-series averages and *t*-statistics in the second row over the period from January 1956 to December 1994, since each company has fewer than 60 observations for estimating parameters in Equation (1) to obtain one-month-ahead predicted returns before January 1956.

	A_t		B_t		X_t	
	average	*t*-stat	average	*t*-stat	average	*t*-stat
1/53 – 12/94	0.39	11.28	0.31	4.49	0.08	1.10
1/56 – 12/94	0.38	46.06	0.30	4.04	0.08	1.13

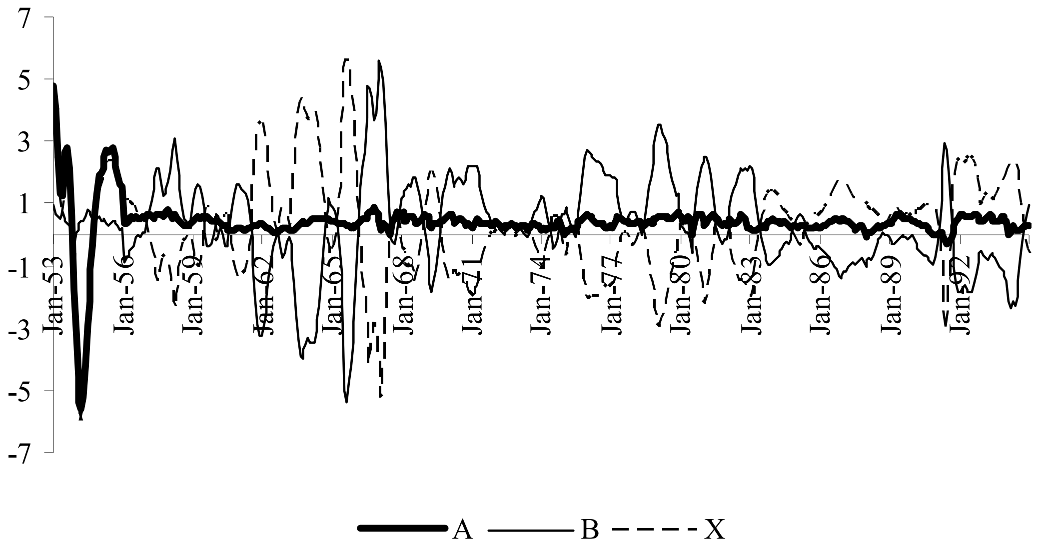

Figure 2.1 A_t**,** B_t**, and** X_t

For each month *t*, I calculate A_t, B_t, and X_t as described in Table 2. Under Assumption 1, i.e. the macroeconomic variables are independent of stocks returns and stock returns follow white noise processes, predicted momentum profit by the macroeconomic variables with intercepts for month *t*, $\hat{\pi}_t$, is proportional to A_t, and predicted momentum profit without intercepts, $\hat{\pi}_t^{\circ}$, is proportional to B_t. Since $\mathrm{X}_t = \mathrm{A}_t - \mathrm{B}_t$, predicted momentum profit due to intercepts is proportional to X_t.

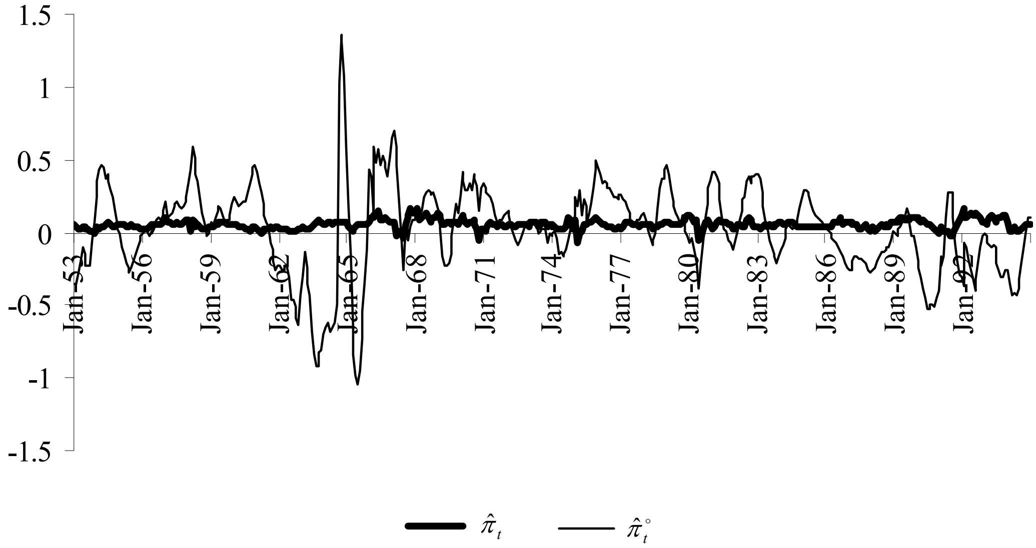

Figure 2.2 Predicted Momentum Profits by the Macroeconomic Variables

For each month t, I calculate predicted momentum profit by the macroeconomic variables with intercepts, $\hat{\pi}_t$, and predicted momentum profit without intercepts, $\hat{\pi}_t^{\circ}$. $\hat{\pi}_t$ and $\hat{\pi}_t^{\circ}$ are defined in Definitions 2 and 2′. Momentum portfolios are constructed based on previous six-month cumulative raw returns as in Definition 1. Returns on stocks in momentum portfolios are predicted by $r_{it} = c_{0i} + \sum_{k=1}^{4} c_{ik} z_{kt-1} + e_{it}$, where $\mathbf{z}_t$ a 1×4 vector of realizations of the macroeconomic variables at the end of time t. Parameters are estimated using data from t-60 to t-1. Predicted momentum profits with intercepts for month t are predicted returns on the momentum portfolio for month t. Predicted momentum profits without intercepts for month t is predicted returns on momentum portfolio excluding intercept estimates.

Table 2.4 Raw, Predicted, and Predicted-Return-Adjusted Momentum Profits

Momentum portfolios are constructed in the manner described in Table 1. Raw momentum profits (π_t) are returns on the momentum portfolios. Predicted profits with intercepts ($\hat{\pi}_t$) and without intercepts ($\hat{\pi}_t^{\circ}$) are calculated in the same manner as in Figure 2 and defined in Definitions 2 and 2′. Finally, adjusted profits with intercepts and without intercepts are predicted-return-adjusted momentum profits with (π_t^a) and without ($\pi_t^{\circ a}$) intercepts defined in Definitions 3 and 3′. So $\pi_t^a = \pi_t - \hat{\pi}_t$ and $\pi_t^{\circ a} = \pi_t - \hat{\pi}_t^{\circ}$. In panel A, the column titled "P10-P1" gives time-series averages of π_t , $\hat{\pi}_t$, $\hat{\pi}_t^{\circ}$, π_t^a , and $\pi_t^{\circ a}$ and *t*-statistics of them in parentheses. On the column titled "#<0", the numbers of months when the momentum profits are negative out of total months in the sample periods and the percentages (in parentheses) that momentum profits are negative are presented. In panel B, the column titled "Ave. Dev." gives average absolute deviations between raw momentum profits and predicted momentum profits with or without intercepts. On the column titled "# diff", the numbers of months when raw momentum profits and predicted momentum profits have different signs and the percentages (in parentheses) are presented.

	1/53 - 12/94		1/53 - 6/63		7/63 - 12/94	
Panel A: Momentum Profits						
	P10 - P1 (*t*)	#<0 (%<0)	P10 - P1 (*t*)	#<0 (%<0)	P10 - P1 (*t*)	#<0 (%<0)
Raw Momentum Profits (π_t)	0.71	160/504	0.89	40/126	0.64	120/378
	(3.03)	(31.75)	(3.11)	(31.75)	(2.18)	(31.75)
Predicted Profits w. int. ($\hat{\pi}_t$)	5.51	13/504	4.02	2/126	5.60	11/378
	(38.38)	(2.58)	(21.30)	(1.59)	(34.60)	(2.91)
Predicted Profits w.o. int. ($\hat{\pi}_t^{\circ}$)	2.27	218/504	3.41	51/126	1.90	167/378
	(1.67)	(43.25)	(1.45)	(40.48)	(1.16)	(44.18)
Adjusted Profits w. int. (π_t^a)	-4.81	426/504	-3.16	101/126	-5.36	325/378
	(-16.97)	(84.52)	(-8.66)	(80.16)	(-15.16)	(85.98)
Adjusted Profits w.o. int. ($\pi_t^{\circ a}$)	-1.58	279/504	-2.64	74/126	-1.23	205/378
	(-1.13)	(55.36)	(-1.10)	(58.73)	(-0.73)	(54.23)
Panel B: Difference Between Raw Momentum Profits and Predicted Momentum Profits						
	Ave. Dev.	# diff (% diff)	Ave. Dev.	# diff (% diff)	Ave. Dev.	# diff (% diff)
Predicted Profits w. int.	5.88	167/504	3.92	42/126	6.33	125/378
		(33.13)		(33.33)		(33.07)
Predicted Profits w.o. int.	23.44	234/504	21.83	59/126	23.84	175/378
		(46.43)		(46.83)		(46.30)

Table 2.5 Regressions of Raw Momentum Profits on Predicted Profits and Predicted Momentum Profits on A_t and B_t.

For each month *t*, raw momentum profits, predicted momentum profits with and without intercepts are calculated in the manners described in Table 1 and Figure 2. A_t and B_t are calculated as in Table 2. In Panel A, I regress raw momentum profits on predicted momentum profits with intercepts in the first row ($\pi_t = \alpha_1 + \beta_1 \hat{\pi}_t + \eta_{1t}$) and on predicted momentum profits without intercepts in the second row ($\pi_t = \alpha_2 + \beta_2 \hat{\pi}_t^{\circ} + \eta_{2t}$) over the period from January 1953 to December 1994. In panel B, predicted momentum profits with intercepts are regressed on A_t ($\hat{\pi}_t = \alpha_3 + \beta_3 \mathrm{A}_t + \eta_{13}$), and predicted momentum profits without intercepts are regressed on B_t ($\hat{\pi}_t = \alpha_4 + \beta_4 \mathrm{A}_t + \eta_{43}$) over the period from January 1956 to December 1994. Under the assumption that the macroeconomic variables are independent of stocks returns and stock returns follow white noise processes (Assumption 1), expectation of predicted momentum profits for month *t* conditional on the realizations of the macroeconomic variable up to month *t*-1 are proportional to A_t, if intercepts are included in predicting momentum profits, and B_t, if intercepts are excluded.

Panel A: Raw Momentum Profits Regressed on Predicted Momentum Profits

	α	β	R^2 (%)
Predicted Profits w. int. ($\hat{\pi}_t$)	0.0072	-0.0026	0.61
	(1.26)	(-1.69)	
Predicted Profits w.o. int. ($\hat{\pi}_t^{\circ}$)	0.0077	-0.0007	0.00
	(3.06)	(-0.05)	

Panel B: Predicted Momentum Profits Regressed on A_t and B_t

	α	β	R^2 (%)
Predicted Profits w. int. ($\hat{\pi}_t$) on A_t	0.0074	0.1281	52.87
	(3.12)	(22.89)	
Predicted Profits w.o. int. ($\hat{\pi}_t^{\circ}$) on B_t	-0.0202	0.1501	60.03
	(-2.20)	(26.48)	

Table 2.6 Cross-Sectional Covariance between Previous Six-Month Returns and Predicted Returns from Simulated Macroeconomic Variable

Under Assumption 2, the z follows a first-order autoregressive process, $z_t = a_0 + az_{t-1} + \varepsilon_{zt}$, where $0 < a <$ 1 and its unconditional expectation is denoted to be μ_z, so $\mu_z = a_0/(1+a)$. Under Assumptions 3 stock returns follow white noise processes and independent of the hypothetical macroeconomic variable. Under Assumptions 2 and 3, I showed that $E\left[\overline{\mathrm{cov}}\left(\hat{r}_t, r_{t-}^m\right)\right] = E(C_t)\Sigma$, where $\Sigma \equiv (N-1)/N^2 \sum_{k=1}^{N} \sigma_k^2$ and $C_t \equiv m/T + \left(z_{t-1} - \bar{z}_{t-2}\right)\sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_{t-2}\right) \Big/ \sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_{t-2}\right)^2$, and that $E\left[\overline{\mathrm{cov}}\left(\hat{r}_t^{\circ}, r_{t-}^m\right)\right] = E(D_t)\Sigma$, where $D_t \equiv z_{t-1} \sum_{j=1}^{m}\left(z_{t-1-j} - \bar{z}_t\right) \Big/ \sum_{j=1}^{T}\left(z_{t-1-j} - \bar{z}_t\right)^2$. For each choice of a and μ_z, I simulate a time-series of hypothetical macroeconomic variable, z, following Assumption 2 from t = -200 to t = 61 with $\sigma_{\varepsilon z}$ = 0.27. I discard first 201 z values from t = -200 to t = 0. Then I calculate C and D using remaining values. I repeat this procedures 10,000 times so I have 10,000 values of C and D for each pair of a and μ_z. Sample averages and standard deviations of the values of C and D are reported.

	a = 0.1		a = 0.3		a = 0.5		a = 0.7		a = 0.9	
	C	*D*	*C*	*D*	*C*	*D*	*C*	*D*	*C*	*D*
mu = 0										
mean	0.1019	0.0018	0.1063	0.0063	0.1158	0.0153	0.1347	0.0332	0.1808	0.0722
std	0.0443	0.0438	0.0518	0.0514	0.0623	0.0621	0.0830	0.0823	0.1187	0.1208
mu = 1										
mean	0.1017	0.0036	0.1074	0.0100	0.1151	0.0182	0.1342	0.0294	0.1812	0.0667
std	0.0436	0.1665	0.0520	0.1906	0.0630	0.2115	0.0837	0.2195	0.1203	0.2229
mu = 3										
mean	0.1014	-0.0053	0.1067	0.0056	0.1151	0.0033	0.1343	0.0180	0.1824	0.0630
std	0.0433	0.4773	0.0522	0.5461	0.0619	0.5988	0.0828	0.6199	0.1208	0.5860
mu = 5										
mean	0.1020	0.0086	0.1067	0.0178	0.1163	0.0163	0.1343	0.0298	0.1802	0.0715
std	0.0448	0.8052	0.0515	0.9063	0.0636	1.0077	0.0829	1.0402	0.1184	0.9546
mu = 7										
mean	0.1016	-0.0127	0.1070	0.0064	0.1154	0.0262	0.1338	0.0336	0.1810	0.0712
std	0.0439	1.1139	0.0524	1.2711	0.0620	1.3891	0.0810	1.4408	0.1201	1.3570

Table 2.7 Predicted-Return-Adjusted Momentum Profits with Different Parameter Estimation Periods

I estimate the parameters in Equation (1) using two different estimation periods. In Panel A and under the first estimation period scheme, if a momentum portfolio is formed at the beginning of month *t*, parameters are estimated using 60-month observations from *t*-47 to *t*-19 and *t*+12 to *t*+41, and the estimated parameters are used in calculating predicted returns during the holding period. If $\hat{\mathbf{c}}_{it}^{1}$ is denoted to be vector of parameters estimated at month *t* for stock *i*, predicted return for month *t* for stock *i* is $1/6\sum_{j=0}^{5}\mathbf{x}_{t-1}\hat{\mathbf{c}}_{it-j}^{1}$, where $\mathbf{x}_{t-1}$ = [1 DIV_{t-1} $TERM_{t-1}$ YLD_{t-1} DEF_{t-1}]. Predicted-return-adjusted momentum profit is momentum profit minus predicted return on the momentum portfolio (predicted momentum profit). I also report predicted-return-adjusted momentum profit without intercept as CS do in their Table III. For this, predicted momentum profits are calculated without intercepts. Under the second estimation period scheme, all procedures are the same as the first one except that parameters are estimated using 60-month observations from *t*-72 to *t*-13 when a momentum portfolio is formed at the beginning of month *t*.

In Panel B, all procedures are same as in Panel A except that predicted returns are estimated with Equation (1) plus January dummy as described in Table 1. In order to be included in momentum portfolios, the stocks have at least 24-month observations for estimating parameters when the momentum portfolios are formed. Under the first estimation period scheme, time-series averages and *t*-statistics (in parentheses) of the predicted-return-adjusted momentum profits are reported over the periods, 1/51-12/94, 1/51-6/63, and 6/63-12/94. Under the second estimation period, sample periods are 6/54-12/94, 6/54-6/63, and 7/63-12/94. The differences in sample periods are due to the 24-month observation requirement.

Finally, Panel C presents raw momentum profits for the subsample of stock-months used in each parameter estimation scheme.

Table 2.7 Continued

	Estimation Period 1			Estimation Period 2	
	P10-P1 w. int.	P10-P1 w.o. int.		P10-P1 w. int.	P10-P1 w.o. int.
Panel A: Adjusted Profits-Business Cycle Model Excludes January Dummy					
1/51-12/94	0.64	-1.44	6/54 -12/94	0.71	2.14
	(2.77)	(-2.42)		(2.80)	(3.05)
1/51-6/63	0.71	0.59	6/54 -6/63	0.79	-4.00
	(2.42)	(0.41)		(2.20)	(-3.67)
7/63-12/94	0.61	-2.25	7/63 - 12/94	0.69	3.90
	(2.03)	(-3.74)		(2.22)	(4.74)
Panel B: Adjusted Profits-Business Cycle Model Includes January Dummy					
1/51-12/94	0.77	-0.64	6/54 -12/94	0.79	1.81
	(3.59)	(-1.18)		(3.19)	(2.61)
1/51-6/63	0.64	1.99	6/54 -6/63	0.86	-3.29
	(2.26)	(1.48)		(2.47)	(-3.24)
7/63-12/94	0.82	-1.69	7/63 - 12/94	0.78	3.28
	(2.95)	(-3.16)		(2.55)	(3.96)
Panel C: Raw Profits					
1/51-12/94	0.68		6/54 -12/94	0.62	
	(3.09)			(2.58)	
1/51-6/63	0.81		6/54 -6/63	0.82	
	(3.23)			(2.70)	
7/63-12/94	0.63		7/63 - 12/94	0.56	
	(2.15)			(1.89)	

Table 2.8 Estimation of First-Order Autoregressive Equation for the Macroeconomic Variables

I estimate $z_t = a_0 + b \cdot t + \nu_t$, where $\nu_t = a \cdot \nu_{t-1} + \varepsilon_t$, for z = *DIV*, *TERM*, *YLD*, and *DEF* over the period from January 1951 to December 1994 with maximum likelihood method. Maximum likelihood estimators and *t*-statistics (in parentheses) for a_0, b, and a. Also, maximum likelihood estimator of standard deviation of residuals is presented.

	a_0	b	a	σ_ε
DIV	4.89	-0.0037	0.98	0.17
	(7.14)	(-1.75)	(127.49)	
TERM	0.31	0.0032	0.9523	0.36
	(0.51)	(1.62)	(72.44)	
YLD	2.28	0.0097	0.98	0.45
	(1.42)	(1.91)	(114.02)	
DEF	0.60	0.0010	0.96	0.09
	(3.03)	(1.54)	(80.84)	

Table 2.9 Momentum Profits Adjusted for Returns Predicted by Random Macroeconomic Variables

I generate four sets of random variables that follow the autoregressive processes estimated in Table 8 for *t* = -100, …, 528. After discarding first 101 values, I calculate momentum profits adjusted for returns predicted by these random variables with and without intercepts in the manner described in Table (1), over the sample periods 1/53-12/94, 1/53-6/63, and 7/63-12/94. *t*-statistics are reported in parentheses.

	1/53 - 12/94		1/53 - 6/63		7/63 - 12/94	
	w. intercept	w.o. intercept	w. intercept	w.o. intercept	w. intercept	w.o. intercept
1	-4.38	-0.89	-3.36	7.16	-4.72	-3.57
	(-16.51)	(-1.01)	(-10.28)	(6.2)	(-14.09)	(-3.33)
2	-4.58	0.42	-3.24	-4.01	-5.03	1.89
	(-16.78)	(0.52)	(-8.77)	(-3.3)	(-14.8)	(1.92)
3	-4.11	-2.73	-2.93	-7.03	-4.50	-1.30
	(-15.23)	(-2.72)	(-8.7)	(-6.4)	(-13.26)	(-1.01)
4	-4.64	-8.31	-3.16	-8.58	-5.14	-8.21
	(-16.71)	(-9.45)	(-9.12)	(-5.93)	(-14.74)	(-7.68)
5	-4.62	-0.47	-2.37	-1.07	-5.37	-0.27
	(-17.3)	(-0.61)	(-7.67)	(-0.82)	(-16.16)	(-0.29)
6	-4.79	1.38	-3.42	-3.04	-5.24	2.85
	(-18.11)	(1.58)	(-10.16)	(-3.11)	(-15.84)	(2.57)
7	-4.94	-2.53	-3.39	-5.69	-5.46	-1.47
	(-17.92)	(-3.17)	(-10.18)	(-6.71)	(-15.74)	(-1.45)
8	-4.61	-2.83	-3.38	0.24	-5.02	-3.86
	(-17.12)	(-3.60)	(-9.65)	(0.22)	(-14.90)	(-3.95)
9	-4.59	-3.29	-3.57	-0.83	-4.93	-4.11
	(-17.4)	(-4.04)	(-11.54)	(-0.65)	(-14.73)	(-4.12)
10	-4.92	-2.11	-3.17	0.29	-5.50	-2.91
	(-18.22)	(-3.24)	(-9.57)	(0.33)	(-16.3)	(-3.58)
Average	-4.62	-2.14	-3.20	-2.25	-5.09	-2.10
	(-17.13)	(-2.57)	(-9.56)	(-2.02)	(-15.06)	(-2.09)
Maximum	-4.11	1.38	-2.37	7.16	-4.50	2.85
	(-15.23)	(1.58)	(-7.67)	(6.2)	(-13.26)	(2.57)
Minimum	-4.94	-8.31	-3.57	-8.58	-5.50	-8.21
	(-18.22)	(-9.45)	(-11.54)	(-6.71)	(-16.3)	(-7.68)

Table 2.10 Holding Period Returns for Two-Way Sorted Portfolios

This table compares CS' Table VII and replicating results with the macroeconomic variables that I have. In Panel A, at the beginning of each month *t*, all stocks are first sorted into quintiles by their past six-month cumulative raw returns. Stocks in each quintile are then assigned to one of five equal-sized portfolios based on their predicted returns from a business cycle model as in Equation (1) 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: $r_{it} = c_{0i} + \sum_{k=1}^{4} c_{ki} z_{t-1} + e_{it}$, where z_{kt} is the realization of the k^{th} macroeconomic variable at month *t*. This regression is run 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 only for differences. The column titled "CS" presents CS' results in their Table VII and the column titled "P" reports my results.

	Raw Returns													
	(low) 1		2		3		4		(high) 5		(5)-(1)		*t*-stat	
	CS	*P*	CS	*P*	CS	*P*	CS	*P*	CS	*P*	CS	*P*	CS	*P*
Panel A: Sorted First by Past Raw Returns and Then by Predicted Returns														
1(low)	1.08	*0.92*	1.08	*1.03*	1.15	*1.10*	1.16	*1.11*	1.28	*1.25*	0.20	*0.33*	0.61	*1.04*
2	0.94	*0.92*	1.14	*1.10*	1.18	*1.12*	1.25	*1.21*	1.37	*1.33*	0.43	*0.41*	1.66	*1.64*
3	1.13	*1.05*	1.27	*1.23*	1.31	*1.24*	1.30	*1.29*	1.55	*1.56*	0.42	*0.50*	1.87	*2.22*
4	1.18	*1.13*	1.35	*1.35*	1.42	*1.36*	1.45	*1.43*	1.71	*1.70*	0.53	*0.56*	2.31	*2.50*
5(high)	1.30	*1.27*	1.44	*1.42*	1.53	*1.47*	1.55	*1.50*	1.72	*1.77*	0.44	*0.51*	1.97	*2.35*
(5)-(1)	0.22	*0.35*	0.36	*0.38*	0.39	*0.38*	0.40	*0.39*	0.46	*0.53*				
t-stat	0.86	*1.48*	3.17	*3.67*	3.57	*3.75*	3.46	*3.69*	3.46	*4.20*				
Panel B: Sorted First by Predicted Returns and Then by Past Raw Returns														
1(low)	1.04	*0.87*	1.02	*0.98*	1.08	*1.05*	1.12	*1.07*	1.18	*1.12*	0.14	*0.25*	0.45	*0.79*
2	1.10	*1.04*	1.21	*1.15*	1.14	*1.10*	1.16	*1.15*	1.30	*1.23*	0.19	*0.20*	1.06	*1.06*
3	1.20	*1.14*	1.28	*1.24*	1.28	*1.24*	1.27	*1.23*	1.33	*1.32*	0.13	*0.17*	0.71	*0.99*
4	1.35	*1.32*	1.44	*1.41*	1.46	*1.44*	1.44	*1.43*	1.61	*1.58*	0.26	*0.26*	1.44	*1.42*
5(high)	1.38	*1.32*	1.51	*1.45*	1.54	*1.53*	1.67	*1.65*	1.78	*1.82*	0.40	*0.50*	1.99	*2.46*
(5)-(1)	0.34	*0.45*	0.29	*0.47*	0.46	*0.48*	0.55	*0.58*	0.60	*0.70*				
t-stat	1.12	*1.60*	2.59	*2.59*	2.76	*2.93*	3.36	*3.70*	3.82	*4.63*				

Table 2.11 Cross-Sectional Correlation Coefficient between Predicted Returns and *m*-Month Lagged Returns

Time-series average of $A_t(m)/m^{1/2}$ for various *m* is reported. $A_t(m) \equiv \mathbf{x}_{t-1}(\mathbf{X}'_{t-2}\mathbf{X}_{t-2})^{-1}\mathbf{X}'_{t-2}\boldsymbol{\iota}^*_m$ over the period from January 1953 to December 1994. I showed that the cross-sectional correlation coefficient between the one-month-ahead predicted returns from the macroeconomic variables and previous *m*-month returns, $\overline{\rho}_m$, is proportional to $E[A(m)]/m^{1/2}$.

m	3	4	5	6	7	8	9
$E[A(m)]/m^{1/2}$	0.2078	0.2193	0.2261	0.2297	0.2316	0.2326	0.2341
m	10	11	12	13	14	15	16
$E[A(m)]/m^{1/2}$	0.2340	0.2337	0.2324	0.2299	0.2258	0.2208	0.2106

Table 2.12 Holding Period Returns for Two-Way Sorted Portfolios with 12-Month Portfolio Formation Period

This table constructed in the same manner as Table 10 except for portfolio formation period. Stocks are sorted by their previous 12-month cumulative raw returns and predicted returns while stocks are sorted by their previous 6-month cumulative raw returns and predicted returns in Table 10 and the portfolios are held for the next six months in both Table 2.10 and this table. All predicted returns are calculated with my macroeconomic variables.

	Raw Returns						
Predicted Returns	(low) 1	2	3	4	(high) 5	Difference (5) - (1)	*t*-statistic (5) - (1)
Panel A: Sorted First by Past Raw Returns and Then by Predicted Returns							
1(low)	1.00	1.19	1.29	1.40	1.69	0.69	2.05
2	0.93	1.07	1.18	1.40	1.56	0.63	2.18
3	0.87	1.13	1.19	1.37	1.70	0.83	3.36
4	1.10	1.23	1.31	1.39	1.67	0.57	2.38
5(high)	0.98	1.15	1.30	1.41	1.59	0.61	2.54
Difference (5)-(1)	-0.02	-0.04	0.01	0.01	-0.09		
t-stat, (5) - (1)	-0.07	-0.35	0.09	0.05	-0.73		
Panel B: Sorted First by Predicted Returns and Then by Past Raw Returns							
1(low)	0.87	1.01	1.11	1.31	1.53	0.66	1.85
2	0.94	1.09	1.11	1.25	1.50	0.56	2.81
3	1.07	1.22	1.22	1.32	1.51	0.45	2.39
4	1.14	1.32	1.35	1.43	1.70	0.56	2.80
5(high)	1.06	1.28	1.44	1.54	1.74	0.67	2.87
Difference (5)-(1)	0.20	0.27	0.33	0.22	0.21		
t-stat, (5) - (1)	0.63	1.33	1.86	1.36	1.31		

Table 2.13 Holding Period Returns for Two-Way Sorted Portfolios with 9-Month Portfolio Formation Period

This table constructed in the same manner as Table 12 except for portfolio formation period. Stocks are sorted by their previous 9-month cumulative raw returns and predicted returns. The portfolios are held for the next six months.

	Raw Returns						
Predicted Returns	(low) 1	2	3	4	(high) 5	Difference (5) - (1)	*t*-statistic (5) - (1)
Panel A: Sorted First by Past Raw Returns and Then by Predicted Returns							
1(low)	0.90	1.05	1.20	1.34	1.57	0.67	2.11
2	0.85	1.07	1.16	1.30	1.52	2.59	0.67
3	0.90	1.12	1.20	1.36	1.71	3.42	0.81
4	1.06	1.24	1.30	1.47	1.73	2.93	0.67
5(high)	1.04	1.29	1.35	1.47	1.79	3.29	0.74
Difference (5)-(1)	0.14	0.24	0.15	0.13	0.22		
t-stat, (5) - (1)	0.59	2.13	1.53	1.27	1.71		
Panel B: Sorted First by Predicted Returns and Then by Past Raw Returns							
1(low)	0.77	0.95	1.09	1.29	1.44	0.47	2.01
2	0.93	1.09	1.14	1.17	1.41	0.48	2.60
3	1.07	1.22	1.22	1.30	1.46	0.39	2.14
4	1.16	1.34	1.37	1.49	1.70	0.54	2.85
5(high)	1.16	1.35	1.47	1.64	1.86	0.70	3.23
Difference (5)-(1)	0.39	0.40	0.39	0.44	0.42		
t-stat, (5) - (1)	1.29	2.15	2.24	2.65	2.67		

Part 3.   Moving Average Ratio and Momentum

I. Introduction

One of the most puzzling phenomena in financial market is intermediate-term momentum in stock prices documented by Jegadeesh and Titman (1993). Jegadeesh and Titman show that the self-financing strategy that buys winners and sells losers based on the previous 3- to 12-month returns and holds the position for the following 3 to 12 months generates positive profits. Rouwenhorst (1998) finds momentum phenomena are not restricted to the US market and prevail in 12 other countries. Also, Jegadeesh and Titman (2001) show that momentum strategies continue to be profitable in 1990s. These results suggest that the profitability of momentum strategies is not the result of data snooping. In addition to intermediate-term momentum, DeBondt and Thaler (1985), Lee and Swaminathan (2000), and Jegadeesh and Titman (2001) document long-term reversals in stock returns. For instance, Jegadeesh and Titman (2001) show that profits from a momentum strategy with 6 months of formation period over a 48-month period starting on the 13th month after the momentum portfolio formation period are significantly negative while momentum profits over a 12-month period immediately after the formation period are significantly positive for the sample period from 1965 to 1997.

Some explanations for intermediate-term momentum in stock prices are consistent with the efficient market hypothesis. For instance, Berk, Green, and Naik (1999) develop a theoretical model that predicts intermediate-term momentum profits. In their model, time-varying but persistent systematic risk generates momentum profits. Conrad and Kaul (1998) show that intermediate-term momentum profits mainly come from the cross-sectional dispersion of unconditional expected returns, while Jegadeesh and Titman

(2001) argue that the results in Conrad and Kaul are driven by estimation errors in the estimation of unconditional expected returns. Finally, Chordia and Shivakumar (2002) argue that a set of macroeconomic variables may predict expected stock returns. However, the second part of this dissertation shows that a spurious relation between persistent macroeconomic variables and predicted returns from the macroeconomic variables falsely appears to explain the momentum.

Barberis, Shleifer, and Vishny (BSV, 1998), Daniel, Hirshleifer, and Subrahmanyam (DHS, 1998), and Hong and Stein (HS, 1999) present behavioral models that attempt to explain the coexistence of intermediate-term momentum and long-term reversals in stock returns. In sum, under BSV, and HS, investors tend to underreact to new information resulting in intermediate-term momentum, but they overcorrect for previous mispricing leading to long-term reversals. Under DHS, momentum occurs because investors tend to overreact to prior information and reversals occur when they correct the mispricing. BSV and DHS attribute psychological biases such as conservatism and representativeness heuristics or overconfidence to the mispricing that leads to momentum or reversals, while HS emphasize the slow diffusion of information to explain momentum.

In addition to the above formal behavioral theories, George and Hwang (GH, 2004) find that the nearness to the 52-week high price can explain a large portion of the profits from momentum strategies. Specifically, GH show that the investment strategy that buys stocks with a high ratio of the current price to the 52-week high and sells stocks with low a ratio produces significantly positive profits. More importantly, the profits from

Jegadeesh and Titman's style momentum strategy are significantly reduced once stock returns are controlled for returns forecasted by the nearness to the 52-week high. GH suggest that investors are subject to an anchoring bias where they use the 52-week high as a reference point against which they evaluate the potential impact of news. When good news has pushed a stock's price near or to a new 52-week high, investors are reluctant to bid the price of the stock higher even if the information warrants it. On the other hand, when bad news pushes a stock's price far from its 52-week high, investors are initially unwilling to sell the stock at prices that are as low as the information implies. The subsequent corrections of these mispricings generate momentum profits.

GH find, however, that the nearness to the 52-week high fails to explain negative profits from Jegadeesh and Titman's momentum strategy over the post-holding periods. This combined with results described in the previous paragraph suggests that a large portion of intermediate-term momentum is caused by investors' anchoring bias on the 52-week high for estimating the current fundamental value, but the anchoring bias has nothing to do with long-term reversals in stock returns. Therefore, GH conclude that intermediate-term momentum and long-term reversals are separate phenomena as opposed to BSV, DHS, or HS.

As main contributions to the momentum literature, I find that the ratio of two variables that are commonly used in technical analysis-the 50-day moving average price and 200-day moving average price-has significant predictive power for future returns and this predictive power is distinct from the predictive power of either past returns or the nearness to the 52-week high. An investment strategy that ranks all stocks based on the ratio of the 50-day moving average to the 200-day moving average and buys equally the top 10% or 30% of stocks and sells the bottom 10% or 30% of stocks produces significant profits for the next 6-month holding period for the sample period from January 1964 to December 2004. Further, I show that the predictive power of stock returns in the previous 6 to 12 months becomes insignificant once future returns are controlled for the future returns forecasted by the ratio of the moving averages and the nearness to the 52-week.

One of the trading rules used in technical analyses suggests that investors buy stocks when the 50-day moving average line crosses the 200-day moving average line from below and sell stocks when the 50-day MA line crosses the 200-day MA line from above. However, it also suggests that if the 50-day MA is much higher than the 200-day MA (which happens with a fast run up in price), a technician might consider this an indication that the stock is temporarily overbought (therefore, overvalued) which is bearish for the short-run. Similarly, if the 50-day MA is much lower than the 200-day MA, it might be considered a signal of an oversold (undervalued) stock, which is bullish for the short-run.[19] I do not test the usefulness of the buy or sell signal when the 50-day and 200-day MA lines cross each other. Instead, I test whether the difference between the 50-day and 200-day MA lines has predictive power for future returns as the technical trading rule suggests. My results are opposite what the technical trading rule suggests; stocks whose

[19] Reilly and Norton (2003) pp 601-602.

50-day MA is much higher than the 200-day MA tend to perform better than stocks whose 50-day MA is much lower than the 200-day MA for the following 6-month period.

These findings, as well as those of George and Hwang, can be explained by investors' anchoring bias as summarized by Kahneman, Slovic, and Tversky (1982). Investors may use the long-term moving average (200-day MA) as a reference point for a long-term fundamental value. Next, they may use a shorter-term moving average (50-day MA) as a reference point for a current price level in order to eliminate noise potentially included in the current price. Investors anchor on the long-term moving average when they evaluate the appropriateness of the current price level. This anchoring on past moving averages is a bias since if the fundamental value follows a random walk process, as most financial theories assume, time-series averages do not have any predictive power for future values. When recent good news has boosted the 50-day MA high above the 200-day moving MA, demand for the stocks would be less than the information warrants because investors falsely believe that the current price level is too high given their anchor, the 200-day MA. This reduction of demand results in underreaction to the information. However, the information eventually prevails and the mispricing is corrected in the subsequent period, resulting in momentum profits. The underreaction is most significant when the difference between the 50-day and 200-day MAs is largest. Similarly, when recent bad news has pushed down the 50-day MA low below the 200-day MA, demand on the stock would be higher than the information indicates because investors falsely believe that the current price level is too low given their anchor, leading to underreaction and momentum. If some investors regard the 52-week high price as their reference point for estimating the fundamental value as George and Hwang (2004)[20] argue, it can be also true that the same investors or other investors use moving averages as their reference points.

Finally, like future returns forecast based on the nearness to the 52-week high in George and Hwang, future returns forecast based on the moving-average ratio do not reverse in the long run, while there are long-term reversals when past performance is measured by the returns in the previous 12 months. This confirms George and Hwang's argument that intermediate-term momentum and long-term reversals are not likely to be components of the same phenomenon as modeled by BSV, DHS and HS.

The remainder of this paper is organized as follows. In Section II, I review the related literature. Section III contains methodology and data. In Section IV, I present results of the paper and Section V concludes.

II. Literature Review

II.A. Intermediate-Term Momentum and Long-Term Reversals

II.A.1. Intermediate-term (3- to 12-month) momentum

II.A.1.a) Trading strategy

First let's define the momentum strategy first developed by Jegadeesh and Titman (1993); I will use this definition throughout this part of the dissertation.

[20] I review George and Hwan (2004) in the next section in detail.

Definition 1: JT momentum strategy, JT(p,J,D,K)

At the beginning of month t, JT (p, J, D, K) sorts all stocks in the sample based on the buy-and-hold returns for the J months from t – D – J to t – D – 1, buys an equally weighted portfolio of the top p% of stocks (winners) and sells an equally weighted portfolio of the bottom p% of stocks (losers), and holds this position for the next K months. In other words, the momentum portfolio formation period is J months, and the holding period is K months, and there is a D-month gap between the formation and holding periods. To increase the power of their tests, JT include portfolios with overlapping holding periods. Therefore, the strategy holds K different momentum portfolios at month t. Momentum profit at month t from the JT momentum strategy is defined to be the average of the returns on the K momentum portfolios at month t.

II.A.1.b) Profits

JT use different combinations of *J*s and *K*s: J = 3, 6, 9, and 12 and K = 3, 6, 9, and 12 for p = 10% and D = 0 or 1 week. Jegadeesh and Titman (1993) document the profits from the 32 different momentum strategies defined above over the period from1965 to 1989 using stocks traded on the NYSE and AMEX from the CRSP daily returns file. The profits of all the momentum strategies are positive. All these profits are statistically significant except for the *JT*(10,3,0,3).

The most successful zero-cost strategy selects stocks based on their returns over the previous 12 months and then holds the portfolio for 3 months: *JT*(10,12,*D*,3). This strategy yields 1.31% per month when there is no time lag between the portfolio formation period and the holding period, i.e., $D = 0$, and it yields 1.49% per month when there is a 1-week lag between the formation period and the holding period, , i.e., $D = 1$ week. The 6-month formation period produces profits of about 1% per month regardless of the holding period. These profits are slightly higher when there is a 1-week lag between the formation period and the holding period than when the formation and holding periods are contiguous.

II.A.1.c) Robustness of momentum

Since Jegadeesh and Titman (1993) first documented intermediate-term momentum in stock returns, two important pieces of evidence have been documented suggesting that the positive profits from the Jegadeesh and Titman momentum strategy are not the result of data snooping. Rouwenhorst (1998) finds that momentum phenomena are not restricted to the US market and prevail in 12 other countries. Also Jegadeesh and Titman (2001) show that momentum strategies continue to be profitable in the 1990s.

II.A.1.d) Industry momentum

Using the CRSP and COMPUSTAT data files, Moskowitz and Grinblatt (MG, 1999) form 20 value-weighted industry portfolios for every month from July 1963 to July 1995. Two-digit SIC codes are used to form industry portfolios. MG implement a 6-month/6-month industry momentum strategy; by sorting the industries from highest and lowest based on their past six-month returns, and investing equally in the top three industries while shorting equally the bottom three industries. This position is held for six months from July 1963 to July 1995.

For comparison purposes, MG also calculate the profits from a 6-month/6-month individual stock momentum strategy similar to Jegadeesh and Titman (1993) except that MG's strategy takes a value-weighted long position in the highest 30 percent of stocks based on the past 6-month returns and a value-weighted short position in the bottom 30 percent of stocks based on the past 6-month returns. (JT's strategy invests equally in the top 10 percent of stocks and shorts the bottom 10 percent of stocks based on the past 6-month returns.)

MG document that the monthly profit from the 6-month/6-month industry momentum strategy and the 6-month/6-month individual stock momentum strategy described in the previous subsection are the same, 0.43 percent per month. They also provide the following evidence:

- Industry portfolios exhibit significant momentum, even after controlling for size, book-to-market equity and individual stock momentum.
- Once returns are adjusted for industry effects, momentum profits from individual equities are significantly weaker and, for the most part, are statistically insignificant.

II.A.2. Long-term (3- to 5-year) reversals

In addition to intermediate-term momentum in stock returns, DeBondt and Thaler (1985) document profits from a long-term contrarian strategy. The authors construct a winner portfolio that consists of the 35 stocks (or 50 stocks) that performed best over the past three years, and a loser portfolio that consists of the 35 stocks (or 50 stocks) that performed worst over the past three years. Loser portfolios significantly outperform the market over the three years after portfolio formation, and winner portfolios earn significantly less than the market three years after portfolio formation. Also, Lee and Swaminathan (2000) show that if there is 2- to 4-year gap between formation period and holding period, the JT momentum strategies yield negative profits using stocks traded on NYSE and AMEX for the sample period from 1965 to 1995. Specifically, They find that $JT(10,J,D,12)$ generates significant losses for $J = 6$ to 12 and $D = 36$ or 48. Combined with Jegadeesh and Titman's findings, this suggests that winner portfolios based on the previous 6- to 12-month returns initially outperform the loser portfolios but the performance of winner and loser portfolios is eventually reversed.

Finally, Jegadeesh and Titman (2001) investigate long-term reversals in stock prices for the sample period from 1965 to 1998. Unlike some of previous momentum literature, they include NASDAQ stocks but exclude all stocks priced below $5 at the beginning of the holding period and all stocks with market capitalizations that would place them in the smallest NYSE decile. They exclude these stocks to ensure that the results are not driven primarily by small and illiquid stocks. For the sample of stocks and period, they report that $JT(10,6,D,12)$ yields significantly negative profits for $D = 12$, 24, 36, and 48.

II.B. Theories and Explanations

While most researchers agree on the existence of intermediate-term momentum and long-term reversals in stock returns, their source has been the subject of controversy. Traditional asset pricing models seem to fail to explain the intermediate-term momentum phenomena. For instance, Jegadeesh and Titman (1993) show that changes in market beta cannot be the source of the intermediate-term momentum and Fama and French (1996) show that the Fama-French three factor model cannot explain the intermediate-term price momentum. Also, the long-term reversals described in the previous subsection persist even after controlling for the Fama-French three-factor risk (Lee and Swaminathan, 2000, and Jegadeesh and Titman, 2001).

Jegadeesh and Titman (1993) initially conjectured that intermediate-term momentum might be driven by investor underreaction to firm-specific information. Since then, many theories to explain intermediate-term momentum and long-term reversals in stock returns based on behavioral models have been suggested. See Barberis, Shleifer, and Vishny (BSV, 1998), Daniel, Hirshleifer, and Subrahmanyam (DHS, 1998), Hong and Stein (HS, 1999) and Barberis and Shleifer (2003). BSV and DHS attribute momentum to investor cognitive biases while HS argue that momentum is due to slow diffusion of firm-specific information to the public. Finally, BS attribute momentum profits to investors' style investing behavior (details in next subsection).

Some explanations for momentum are consistent with the efficient markets hypothesis. There are two classes of such explanations. One argues that momentum strategies systematically buy high-risk stocks and sell low-risk stocks. (See Conrad and Kaul, 1998) The other suggests that momentum strategies tend to buy stocks when the expected returns of the stocks is high and sell stocks when the expected returns of the stocks is low. (See Berk, Green, and Naik, 1999, and Chordia and Shivakumar, 2002) Conrad and Kaul (1998) argue that stocks with high realized returns will be those that have high expected returns, suggesting that the momentum strategy's profitability is a result of cross-sectional variability in expected returns. However, Grundy and Martin (2001) show that the profitability cannot be explained as a reward for bearing risk as measured by the three factors of the Fama-French (1996) model, nor by cross-sectional variability in stocks' average returns. 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 unconditional 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.

It is plausible that intermediate-term momentum profits are due to time-varying risk and hence, due to systematic changes in expected returns. Chordia and Shivakumar (2002) show that the expected returns of momentum portfolios can be predicted by four macroeconomic variables and argue that the macroeconomic variables might be related to risk factors that are not yet identified. However, Part 2 of this dissertation shows that that a spurious relation between persistent macroeconomic variables and predicted returns from the macroeconomic variables falsely appears to explain the momentum.

Behavioral Models for the Intermediate-Term Momentum and Long-Term Reversals

Barberis, Shleifer, and Vishny (BSV, 1998), Daniel, Hirshleifer, and Subrahmanyam (DHS, 1998), and Hong and Stein (HS, 1999) present theoretical models that attempt to explain the coexistence of intermediate-term momentum and long-term reversals in stock returns. In sum, under BSV and HS, momentum occurs because traders underreact when new information arrives and long-term reversals occur because they overcorrect previous mispricing. In DHS, momentum occurs because traders overreact to prior information and the subsequent correction of this overreaction results in long-term reversals.

Barberis, Shleifer and Vishny (BSV, 1998)

BSV explain intermediate-term price momentum and long-term price reversal using a parsimonious model of investor sentiment. Their behavioral model is based on two psychological constructs: *conservatism* and the *representativeness heuristic*. Conservatism states that individuals are slow to change their beliefs in the face of new evidence. Individuals subject to conservatism might disregard the full information content of an earnings announcement, perhaps because they believe that it contains a large temporary component, and still cling, at least partially, to their prior estimates of earnings. As a consequence, they might underreact to new information when evaluating stocks.

The second relevant phenomenon is the representativeness heuristic documented by Tversky and Kahneman (1974): "*A person who follows this heuristic evaluates the probability of an uncertain event according to the degree to which it is (i) similar in its essential properties to the parent population, and (ii) reflects the salient features of the process by which is generated*".[21] When a stock experiences a series of good (poor) performance in the previous period caused by investors' conservatism, thus underreaction, investors falsely conclude that the past history is representative of future returns. As a

[21] Tversky and Kahneman (1974), p. 33.

Formation Period (Month -11 to month 0)	Momentum Strategy Holding Period (Month 1 to month 12)		Post-Holding Period (Month 13 to month 60)
Underreaction	Correction of previous underreaction	Overreaction	Correction of previous overreaction
Conservatism heuristic bias	-	Representativeness heuristic bias	-

Figure 3.1 Summary of BSV's Model

consequence, investors using the representative heuristic might overreact to the history of high (low) returns that is unlikely to repeat itself in evaluating stocks. In summary, they regard the intermediate-term momentum as results of underreaction and the long-term reversals as results of overreaction of the investors.

The empirical findings of intermediate-term momentum and long-term reversals can be explained by BSV in the Figure 3.1, where the holding period starts at month 1.

Daniel, Hirshleifer, and Subrahmanyam (DHS, 1998)

DHS suggest a model that is based on investors' overconfidence and variations in confidence arising from biased self-attribution. If an investor overestimates his ability to judge information, or to identify the significance of existing data that others neglect, he will underestimate his forecast errors. If he is more overconfident about signals or assessments with which he has greater personal involvement, he will tend to be overconfident about the information he has generated but not about public signals. Therefore, stock prices overreact to private information signals and underreact to public signals. They show that this overreaction-correction pattern is consistent with long-run negative autocorrelation in stock returns.

According to attribution theory (Bem, 1965), individuals too strongly attribute events that confirm the validity of their judgment to their own high ability, and events that conflict with their judgment to external noise or sabotage. According to the attribution theory, if an investor receives confirming public information, his confidence rises, but conflicting information causes his confidence to fall only modestly, if at all. Therefore, even if an individual begins with unbiased beliefs about his ability, new public signals on average are viewed as confirming the validity of his private signal. This suggests that public information can trigger further overreaction to a preceding private signal. They show that such continuing overreaction causes momentum in security prices, but that such momentum is eventually reversed as further public information gradually draws the price back toward fundamentals. Thus, biased self-attribution implies that intermediate-term momentum and long-term reversals would be observed. In sum, the authors think of intermediate-term momentum as result of overreaction, and long-term reversals as result of corrections of previous mispricings. Again the empirical findings of intermediate-term momentum and long-term reversals as explained by DHS can be illustrated in Figure 3.2, where the holding period starts at month 1.

Formation Period (Month -11 to month 0)	**Momentum Strategy Holding Period (Month 1 to month 12)**	**Post-Holding Period (Month 13 to month 60)**
-	Overreaction	Correction of previous overreaction
-	Overconfidence reinforced by self-attribution bias	-

Figure 3.2 Summary of DHS's Model

Hong and Stein (HS, 1999)

Alternatively, HS (1999) develop a model that focuses on the interaction between heterogeneous representative agents rather than the psychology of the agents. In other words, less of the action in their model comes from particular cognitive biases, and more of it comes from the way these traders interact with one another. Their model employs two types of investors: newswatchers and momentum traders. The newswatchers rely exclusively on their private information; momentum traders rely exclusively on the information in past price changes. The additional assumption that private information diffuses only gradually through the marketplace leads to an initial underreaction to news. The underreaction and subsequent positive serial correlation in returns attracts the attention of the momentum traders whose trading activity results in an eventual overreaction to news. Prices revert to their fundamental levels in the long run. In Hong and Stein (1999), initial momentum comes from underreaction by the news watchers. Later momentum is the result of overreaction by the momentum traders, and the long-term reversal comes from prices reverting to their fundamental values. In their model, HS restrict momentum traders to have simple strategies, that is, momentum traders at time *t* base their trades only on the price change over limited prior intervals, so they do not know whether prices of stocks are still undervalued or have already overshot their long-run equilibrium values. Therefore, momentum traders sometimes gain from their trades, but sometimes lose. The empirical findings for intermediate-term momentum and long-term reversals can be explained by HS in Figure 3.3, where the holding period starts at month 1.

Formation Period (Month -11 to month 0)	Momentum Strategy Holding Period (Month 1 to month 12)		Post-Holding Period (Month 13 to month 60)
Underreaction	Correction of previous underreaction	Overreaction	Correction of previous overreaction
Slow diffusion of information	-	Momentum traders	-

Figure 3.3 Summary of HS's Model

II.C. George and Hwang (2004) and Fama-MacBeth Style Cross-Sectional Regression

II.C.1. 52-week high strategy

George and Hwang (2004, hereafter GH) find that the nearness of the current price to the 52-week high price as measured by the ratio of the current price to the 52-week high explains a large portion of the profits from the JT momentum strategy. GH define the 52-week high strategy as follows

Definition 2: GH 52-week high strategy, GH 52HI(p,D,K)

52HI (p, D, K) is same as the JT (p, J, D, K) except that stocks are ranked based on the ratio of the price at the end of month t – D – 1 to the highest daily stock price during the 12-month period from t – D – 12 to t – D – 1, $P_{i,t-D-1} / high_{i,t-D-1}$, *where* $P_{i,t\text{-}D\text{-}1}$ *is the price of stock i at the end of month t – D – 1 and high* $_{i,t\text{-}D\text{-}1}$ *is the highest price of stock i during the 12-month period that ends on the last day of month t – D – 1. This strategy buys the top p% of stocks that have the highest* $P_{i,t-D-1} / high_{i,t-D-1}$ *ratio and sells bottom p% of stocks and holds this position for the next K months. In other words, there is a D-month gap between the measurement period of the ratio (or formation period) and the holding period. All prices are adjusted for dividends and stock splits when calculating the price* *ratio. Monthly profits from this strategy are simply called "52-week high profits" throughout this part of the dissertation.*

II.C.2. Fama-MacBeth Cross-sectional regression

Let's consider the following cross-sectional regression model for period *t*;

$$\tilde{R}_{it} = \tilde{\gamma}_{0t} + \tilde{\gamma}_{1t} s_{it-1} + \tilde{\varepsilon}_{it}, \tag{1}$$

where $\tilde{R}_{it}$ is stock *i*'s return for period *t* and s_{it-1} is the natural logarithm of stock *i*'s market capitalization at the end of period *t* – 1. I adopt "~" for the stochastic variables following Fama MacBeth (1973) to emphasize that the regression coefficients, γ_{0t} and γ_{1t}, are allowed to vary stochastically from period to period. Also, $\tilde{\gamma}_{0t}$ and $\tilde{\gamma}_{1t}$ are assumed to be temporally identically and independently distributed.

The implication of the CAPM is that $E(\tilde{\gamma}_{1t}) = 0$. Implementation of the Fama-MacBeth approach to test this implication of the CAPM involves two steps. First, given *T* periods of data, Equation (1) is estimated using OLS for each *t*, *t* = 1, …, *T*, giving the *T* estimates of $\tilde{\gamma}_{1t}$, denoted as $\hat{\gamma}_{1t}$. Then in the second step, the time series of $\hat{\gamma}_{1t}$'s is analyzed. Under the assumption that $\tilde{\varepsilon}_{it} \sim N(0, \sigma_{\varepsilon}^2)$ and $\sigma_{st}^2 = c$, where σ_{st}^2 is the cross-section variance of the natural logarithm of the market capitalization at period *t* and *c* is some constant, $\hat{\gamma}_1$ follows identical and independent normal distributions . Hence, given time-series of the estimated regression coefficients, $\hat{\gamma}_{1t}$, for *t* = 1,…, *T*, we can test the null that $E(\tilde{\gamma}_{1t}) = 0$ using the usual *t*-test. GH use a similar methodology testing predictive power of the ratio of the current price to the 52-week high for future returns after controlling for the firm size, one-month lagged returns and the past returns as described in the next subsection. I also follow this methodology when testing the predictive power of the moving-average ratio for the future returns.

II.C.3. Comparisons of JT momentum, MG industry momentum, and GH 52-week high strategies

George and Hwang compare profitability from JT momentum, Moskowitz and Grinblatt (1999) industry momentum, and GH 52-week high strategies using a Fama-MacBeth style cross-sectional regression analysis. Before describing the cross-sectional regression analysis for momentum, I will define the MG industry momentum strategy used by George and Hwang since MG industry momentum strategy used by GH is slightly different from what is done in Moskowitz and Grinblatt (1999).

Definition 3: MG industry momentum strategy, MG (p,J,D,K)

Under MG (p,J,D,K), at the beginning of each month t, the value-weighted industry returns over the past J months, from t – D – J to t – 1 are measured and stocks are ranked according to their industries' past performance. Stocks ranked in the top p% of industries are assigned to the winner portfolio and stocks in bottom p% are assigned to the loser portfolio. These portfolios are equally weighted. This strategy buys the winner portfolio and sells loser portfolio and holds this position for following K months. The remaining procedures are exactly same as JT (p,J,D,K) and 52HI (J,D,K).

II.C.3.a) Fama-MacBeth style cross-sectional regression analysis

GH compares the contributions of the portfolios from the three investment strategies on profits from JT momentum strategy, *JT* (30,6,*D*,*K*), *MG* (30,6,*D*,*K*), and *52HI* (30,*D*,*K*) for D = 1 and K = 6 or 12. In other words, the strategies buy (sell) an equal-weighted portfolio of the 30% of stocks based on the appropriate ranking scheme and hold the positions for the next K months from one month after the formation period (a one-month gap between the formation and holding periods). Their sample includes all stocks traded on NYSE, AMEX, and NASDAQ and the sample period is from July 1963 to December 2001. The functional form of the month t cross-sectional regression that GH analyze is

$$\begin{aligned} R_{it} &= b_{0kt} + b_{1kt} R_{it-1} + b_{2kt} size_{it-1} + b_{3kt} JH_{it-D-k} + b_{4kt} JL_{it-D-k} + b_{5kt} MH_{it-D-k} \\ &\quad + b_{6kt} ML_{it-D-k} + b_{7kt} FHH_{it-D-k} + b_{8kt} FHL_{it-D-k} + e_{it} \end{aligned}, \qquad (2)$$

for $k = 1,\ldots, K$, where R_{it} and $R_{it\text{-}1}$ are stock i's returns for month t and month t -1, $size_{it\text{-}1}$ is market capitalization of stock i at the end of month $t-1$, $JH_{it\text{-}k}$ equals one if stock i's past performance over the 6-month period (t-D-k-5, t-D-k-1) is in the top 30% when measured by JT momentum strategy performance criterion., and is zero otherwise; $JL_{it\text{-}k}$ equals one if stock i's past performance over the period (t-D-k-5, t-D-k-1) is in the bottom 30% when measured by JT momentum strategy performance criterion, and is zero otherwise. The variables *MH* and *ML* (*FHH* and *FHL*) are defined similarly for MG industry momentum strategy (GH 52-week high strategy). Since the returns to *JT* (30,6,*D*,*K*), *MG* (30,6,*D*,*K*), and *52HI* (30,*D*,*K*) involve portfolios formed over K of the prior K+D months, the marginal return in month t of the winner and loser portfolios, b_{3t}, …, b_{8t}, can be expressed as averages, $1/K \sum_{k=1}^{K} b_{3kt}$, …, $1/K \sum_{k=1}^{K} b_{8kt}$, where the individual coefficients, b_{3kt} , …, b_{8kt} , are computed from separate cross-sectional regressions for each $k = 1, \ldots, K$. In other words, $b_{3t} = 1/K \sum_{k=1}^{K} b_{3kt}$, …, $b_{8t} = 1/K \sum_{k=1}^{K} b_{8kt}$. The time-series averages of the month-by-month estimates of these averages and associated *t*-statistics are used to test the predictability of each variable on future returns.

The analysis of regression equation (2) has several advantages. First, it can assess the simultaneous effects of different trading strategies even after controlling for market microstructure effects and size effects. Second, from the difference in estimated coefficients between winner or loser dummies, we can estimate the marginal profitability of an investment strategy in economically meaningful terms. For instance, $b_3 - b_4$ represents the expected monthly profit of a pure *JT* (30,6,*D*,*K*) strategy. The pure JT momentum strategy would be a JT momentum strategy that includes only pairs of stocks, one of which belongs to the JT winner portfolio and the other of which belongs to the JT loser portfolio and both of which are identical in one-month lagged return, size, and membership in any other investment strategies. Finally, we can measure the contributions to the profits from winner and loser portfolios separately. For example, if $b_3 > 0$ and $b_4 = 0$, we can say that JT momentum profits completely come from the winner portfolio.

II.C.3.b) Results

In sum, GH report that the time-series averages of $\hat{b}_3 - \hat{b}_4$, $\hat{b}_5 - \hat{b}_6$, and $\hat{b}_7 - \hat{b}_8$ are significantly positive and the average of $\hat{b}_7 - \hat{b}_8$ is greater than that of $\hat{b}_3 - \hat{b}_4$ or $\hat{b}_5 - \hat{b}_6$ in magnitude and statistical significance for both K = 6 and 12. Results are similar when GH returns are controlled for Fama-French three factors. From these results, GH conclude that the 52-week high strategy dominates the JT momentum and MG industry momentum strategies and conjecture that a large portion of the predictive power of past returns in individual stock level or industry level is in fact due to the predictive power of the nearness of the current price to the 52-week high.

II.C.3.c) Explanations and implications for previous behavioral theories

GH explain these findings as follows. *"Traders use the 52-week high as a reference point against which they evaluate the potential impact of news. When good news has pushed a stock's price near or to a new 52-week high, traders are reluctant to bid the price of the stock higher even if the information warrants it. The information eventually prevails and the price moves up, resulting in a continuation."* In other words, as the price approaches the reference point, underreaction occurs and the subsequent correction of this underreaction results in momentum profits. A similar underreaction to information occurs when the price moves down far below the reference point. GH further argue that price levels are more important determinants of momentum effects than past price changes.

GH further argue that a theory in which price level relative to an anchor plays a role (anchor-and-adjust bias) may be more descriptive of the data than existing theories based on overconfidence, conservatism, or slow diffusion of information that lead to continuations of past returns.

II.C.4. Long-term reversals

GH estimate the regression equation (2) for D = 12, 24, 36, and 48 and K = 12. In other words, they compare the marginal profitability of the three investment strategies when there are 12-, 24-, 36-, and 48-months gap between the formation and the holding periods in order to see whether the intermediate-term profit from each investment strategy persists, reverses, or disappears in the long horizon. GH use risk-adjusted returns for Fama-French risk factors on winner or loser portfolios from the investment strategies for these analyses and they footnote that the results using raw returns are similar. GH find that when the holding periods include all months, the time-series average of $\hat{b}_3 - \hat{b}_4$ (the pure JT momentum risk-adjusted profits) are significantly negative for D = 12 and 48. When Januarys are excluded, the pure JT momentum risk-adjusted profits are significantly negative for D = 12, 36, and 48. The average of $\hat{b}_5 - \hat{b}_6$ (the pure MG industry momentum risk-adjusted profit) is significantly negative for D = 48 when Januarys are included in the holding periods, and significantly negative for D = 12 when Januarys are excluded from the holding periods. However, the average of $\hat{b}_7 - \hat{b}_8$ (the pure GH 52-week high risk-adjusted profit) is not significantly negative at any gap and is significantly positive for D = 12 when Januarys are excluded from the holding periods.

These results suggest that returns predicted by the past returns tend to be reversed 12 months after the portfolio formation period while returns predicted by the 52-week high are permanent.

The results described in Subsection II.C. and the previous paragraph, indicate that intermediate-term return continuations are most strongly related to the nearness to 52-week high price, but long-term reversals are unrelated to the primary driver of intermediate-term return continuation. GH argue that if intermediate-term return continuations and long-term reversals were linked as existing theories of momentum described in Subsection II.B as BSV, DHS, and HS suggest, then reversals should be strongest for stocks exhibiting the strongest bias, i.e., 52-week winners and losers, rather than stocks identified as winners and losers by the JT or MG momentum strategy. Instead, the opposite occurs. GH conclude that the explanation for long-term reversals appears to lie elsewhere, presenting a new challenge for theories.

II.D. Anchoring bias

Tversky and Kahneman (1974) argue that when forming estimates, people often start with some initial, possibly arbitrary value, and then adjust away from it. Experimental evidence shows that the adjustment is often insufficient. In one experiment, subjects were asked to estimate the percentage of United Nations' countries that are African. More specifically, before giving a percentage, they were asked whether their guess was higher or lower than a randomly generated number between 0 and 100. Their subsequent estimates were significantly affected by the initial random number. Those who were asked to compare their estimate to 10, subsequently estimated 25%, while those who compared to 60, estimated 45%. GH argue this anchoring bias to the initial value in the above experiment is analogous to underreaction of stock prices when current prices are extremely close to or extremely far from the 52-week high. When investors are estimating the current fundamental value of a stock, they anchor too much on the arbitrary reference value such as the 52-week high price. If fundamental value follows a random walk, the 52-week high price is in fact an arbitrary value.

II.E. Moving averages

In this part of the dissertation, I introduce two variables that have been widely used in technical analysis; the 50-day moving average and 200-day moving average. An undergraduate textbook introduces a popular technical trading rule as follows.

"*When the 50- and 200-day MA lines cross, it signals a change in the overall trend. If the 50-day MA line crosses the 200-day MA from below on good volume, this would be a bullish indicator (buy signal). .... In contrast, when the 50-day line crosses the 200-day line from above, it signals a change to a negative trend and would be a sell signal. .... If this positive gap (difference between the 50- and 200-MA lines) gets too large, a technician might consider this an indication that the stock is temporarily overbought. .... If the gap was large on the downside, it might be considered a signal of an oversold stock, which is bullish for the short-term.*"[22]

[22] Reilly and Norton (2003) pp 601-602.

Financial researchers are generally skeptical about the usefulness of technical analysis as summarized by Jegadeesh (2002), concluding that technical analysis is a method built on weak foundations and that there is no plausible explanation why technical patterns in asset prices should be expected to repeat themselves. In fact, a technical trading rule that works for some time period often does not work for another time period. For instance, Brook, Lakoishok, and LeBaron (1992) find that trading rules based on moving averages and trading range breaks (support and resistance levels) significantly outperform a cash benchmark by utilizing the Dow Jones Index from 1987 to 1986. However, LeBaron (1999) finds that when 10 more years (1988 – 1999) were added to the original Brook et al. sample, what was once the consistently best performing trading rule failed badly in the most recent decade. Prior tests of the usefulness of technical trading rules based on moving averages used as an indicator variable the time at which a shorter MA line crosses a longer MA line (see Fong and Yong for summary), but as far as I know none of them test for the notion that the large positive (negative) gap between a shorter MA line and a longer MA line indicates a sell (buy) signal. Therefore, this part of the dissertation appears to be the first use of the ratio of a shorter MA to a longer MA in predicting future returns in the academic literature.

III. Methodology and Data

III.A. Investment Strategies

Throughout this part of the dissertation, I compare the profitability of three different trading strategies; *JT* (p, J, D, K) and GH 52*HI* (p, D, K), defined in Definitions 1 and 2, and *MAR* (p, D, K), which is defined as follows.

Definition 4: Moving-Average Ratio strategy, MAR (p, D, K)

At the beginning of each month t, MAR (p, D, K) calculates the average price during 50- and 200-day period ending on the last trading day of month t – D – 1, and the ratio of this 50-day average to the 200-day average (MAR). The method for constructing the investment portfolio and its returns based on MAR, for MAR (p, D, K), is the same as GH 52HI (p, D, K) except that stocks are ranked based on the moving average ratio instead of distance from the 52-week high. This strategy buys equally the top p% of stocks that have highest MAR and sells equally the bottom p% of stocks and holds this position for the next K months. There is a D-month gap between the measurement period of the ratio (or portfolio formation period) and the holding period. As with GH 52HI (p, D, K), all prices are adjusted for dividends and stock splits when calculating the price ratio. Monthly profits from this strategy are simply called "MAR strategy profits" throughout this part of the dissertation.

III.B. Data

I use the CRSP monthly and daily files from July 1962 through December 2004. I use two different data samples. The first sample includes all stocks traded on the NYSE, AMEX, and NASDAQ but excludes all stocks priced below $5 at the end of the formation period and all stocks with market capitalizations that would place them in the smallest NYSE decile. These screening criteria are the same as those used by Jegadeesh and Titman (2001). The second sample is the same as the first one except that the price or size screening is not applied. This sample is the same as the one in George and Hwang

(2004) except for the sample period. I use these two samples in order to see how small and illiquid stocks affect profits from the investment strategies.

When constructing winner or loser portfolios for the three investment strategies at the beginning of month *t*, I exclude stocks according to following observation criteria; stocks that are missing any monthly returns for the previous *J*-month period (*t*-*J*, *t*-1); stocks that have fewer than 200 daily observations for the previous one-year period (*t*-12, *t*-1); stocks that have fewer than 160 daily observations for the previous 200-day period ending on the last trading day of month *t*-1; and stocks that have fewer than 40 daily observations for the previous 50-day period ending on the last trading day of month *t*–1. If a stock is excluded from the formation of a JT momentum strategy, it is also excluded from the other investment strategies even if it meets the observation requirement for the other strategies. If a stock is included in the winner or loser portfolios but is deslisted or has missing observations during the holding period, I assume that its return is the same as the average return on the portfolio. I failed to find how other researchers handled missing observations during the portfolio holding period. However, since I use monthly returns for calculating holding period returns, there are few firms with missing returns for an entire month, so my treatment for missing observations in the holding period does not affect the results too much.

III.C. Fama-MacBeth (1973) Regressions

In order to simultaneously compare the profitability from the three strategies *JT* (*p*, *J*, *D*, *K*), GH 52*HI* (*p*, *D*, *K*), and *MAR* (*p*, *D*, *K*) after controlling for potential market microstructure and size effects, I implement Fama-MacBeth (1973) style cross-sectional regressions in a manner similar to George and Hwang (2004). In order to compare *JT* (*p*, *J*, *D*, *K*), 52*HI* (*p*, *D*, *K*), and *MAR* (*p*, *D*, *K*), where $D > 0$, at each month *t*, I implement *K* cross-sectional regressions as follows;

$$\begin{aligned} R_{it} &= b_{0kt} + b_{1kt} R_{it-1} + b_{2kt} \ln\left(size_{it-1}\right) + b_{3kt} JH_{it-D-k} + b_{4kt} JL_{it-D-k} + b_{5kt} FHH_{it-D-k} \\ &\quad + b_{6kt} FHL_{it-D-k} + b_{7kt} MAH_{it-D-k} + b_{8kt} MAL_{it-D-k} + e_{it} \end{aligned}, \qquad (3)$$

for $k = 1, \ldots, K$, where R_{it}, R_{it-1}, JH_{it-k}, JL_{it-k}, FHH_{it-k} and FHL_{it-k} are defined as in Equation (2) and MAH_{it-k} equals one if stock *i*'s moving average ratio at the end of month $t - D - k - 1$ is in the top *p*% and zero otherwise; MAL_{it-k} equals one if stock *i*'s moving average ratio at the end of month $t - D - k - 1$ is in the bottom *p*% and zero otherwise. I use the natural logarithm of the market capitalization to measure size effects while George and Hwang use the market capitalization itself.[23]

Once the coefficients, b_{lkt} for $l = 0, \ldots, 8$, are estimated for $k = 1, \ldots, K$, I calculate the averages of the estimated coefficients for each *l*, so $\hat{b}_{lt} = 1/T \sum_{k=1}^{K} \hat{b}_{jkt}$ for $l = 0, \ldots, 8$. Also, I calculate $\hat{b}_{3t} - \hat{b}_{4t}$, $\hat{b}_{5t} - \hat{b}_{6t}$, and $\hat{b}_{7t} - \hat{b}_{8t}$ to calculate month-*t* profits from the pure JT momentum, GH 52-week high and MAR strategies. Finally the time-series averages of $\hat{b}_{lt}$'s and $\hat{b}_{3t} - \hat{b}_{4t}$, $\hat{b}_{5t} - \hat{b}_{6t}$, and $\hat{b}_{7t} - \hat{b}_{8t}$, and associated *t*-statistics are used to test for the profitability of the three investment strategies and market microstructure and size effects.

[23] GH do not provide the reason that they use the market capitalization while most researchers use natural logarithm of the market capitalization to measure size effects.

IV. Results

IV.A. Summary statistics

Panel A of Table 3.1of this paper presents the time-series averages of the cross-sectional means and standard deviations of the returns over the past six and 12 months, the ratio of the current price to the 52-week high, and the moving average ratio over the period from January 1964 to December 2004.[24] I exclude all stocks that are priced below $5 and all stocks with market capitalizations that would place them in the smallest NYSE decile. Panel B of Table 3.1 reports the time-series averages of the estimates of the pair-wise correlation coefficients among the four variables. It is not surprising that the four variables are strongly correlated to each other. All of the time-series averages of the correlation coefficient estimates are above 0.5.

IV.B. Profits from the Three Investment Strategies

Table 3.2 presents the average monthly returns of winners, losers, and the winner minus loser portfolios from the three investment strategies, *JT* (p, J, D, K), 52*HI* (p, D, K), and *MAR* (p, D, K) for P = 10% or 30%, J = 6 or 12 months, D = 0, and K = 6 for the 41-year period from 1964 to 2004. All stocks on the NYSE, AMEX, and NASDAQ are included except for stocks that are priced less than $5 or would be in the smallest NYSE decile at the end of formation period. The 2nd through 5th columns show average monthly returns when p = 10% and the 6th through 9th columns show average monthly returns when p = 30%. In panel A, I calculate average monthly returns and associated t-statistics for all months and in panels B and C, I separately show the average monthly returns for non-

[24] All tables of this part of the dissertation are in Appendix 2.

January months and for only Januarys because previous literature indicates momentum profits are significantly different in non-January months and Januarys. Also, in order to see if profits from the investment strategies are dependent on the sample periods, separate average monthly returns for the two subsample periods, January 1964 – December 1983 and January 1984 – December 2004, are reported.

Panel A shows that profits from both JT momentum strategies are economically and statistically significant. For instance, the average monthly profit from *JT*(10,6,0,6) is 1.23% for the entire sample, which is exactly same as Jegadeesh and Titman (2001) report for the sample period from 1965 to 1998 using the same screening criteria. This profit is more economically and statistically significant than what Jegadeesh and Titman (1993) originally report excluding NASDAQ stocks for the sample period from 1965 to 1989 but without price or size screening. This might be because small or illiquid stocks are more subject to short-term (weekly or monthly) reversals possibly caused by market microstructure effects such as bid-ask bounce and liquidity effects and excluding small stocks in my sample reduces the market microstructure effects. For the entire sample period and for all months, the 6-month holding period returns is slightly higher when the formation period is 6 months than when the formation period is 12 months for p = 10%, while the JT momentum strategy with a 12-month formation period is more profitable than that with a 6-month formation period for p = 30%. Monthly profits from JT momentum strategies for both subsample periods are similar in magnitude and statistical significance. This suggests that intermediate-term momentum is not the result of data snooping as Jegadeesh and Titman (2001) argue and that arbitrageurs do not exploit this predictable price behavior once they come to know the arbitrage opportunities as argued by Shleifer and Vishny (1997).

Panel A shows that two other investment strategies, *GH 52HI* (p, 0, 6) and *MAR* ((p, 0, 6), produce economically and statistically significant profits for p = 10% and 30% while the moving-average ratio strategy is most profitable and statistically significant for all subsample periods. For example, when p = 10%, monthly profits from *MAR* (10, 0, 6) is 1.45% with t-statistic of 6.02. The next most profitable strategy is *JT* (10, 6, 0, 6), which produces 1.23% per month with t-statistic of 5.16. The third strategy is *JT* (10,12, 0, 6) (1.21% per month and t-statistic of 4.94) and *GH 52HI* (10, 0, 6) is least profitable (1.15% per month and t-statistic of 4.49). When p = 30%, the order of profitability is the same as when p = 10% except that *JT* (30,12, 0, 6) is more profitable than *JT* (30, 6, 0, 6). Since monthly profits from the GH 52-week high and moving-average strategies are similar for both subsample periods, I may conclude that the success of the 52-week high and moving-average strategies are not restricted to a specific sample period.

Panels B and C contain the same information as Panel A, but Panel B presents average monthly profits from the investment strategies for only Januarys and Panel C reports average monthly profits when Januarys are excluded from the holding periods. Results in Panel B show that profits from the three investment strategies exhibit significant seasonality; profits are all negative in Januarys, which can be explained by investors' tax-loss selling or window dressing behavior. Under the tax-loss selling argument, at the end of the year investors who become more concerned about their income taxes tend to sell stocks on which they have unrealized capital losses more than they would if there were no tax motivation. Therefore, the prices of stocks that have depreciated during the year tend to be below fundamental values at the end of the year because of temporary selling pressure. In early January, the selling pressure for such stocks ceases to exist and their prices return to fundamental values resulting in the positive returns on stocks that have been excessively sold at the end of the previous year. (See Grinblatt and Moskowitz (2004) for summary) Under the window dressing argument, investment companies such as mutual funds may want to purchase (sell) stocks that have performed extremely well (poorly) just before the reporting date to make the portfolio composition look as if the manager chose successful stocks, which is called a window dressing. It seems reasonable to assume that the most important reporting period is the calendar year. This window dressing might make the demand for such stocks temporarily deviate from those in equilibrium. This temporary deviation of demands from those in equilibrium would be released at the beginning of the next year, leading to return reversals in Januarys. Panel B indicates that the GH 52-week strategy is most subject to January return reversals for all sample periods while the MAR strategy is least subject to January return reversals. When Januarys are excluded from the holding periods in Panel C, GH 52-week high strategies are slightly more profitable than JT momentum strategies, while the MAR strategies are still the most profitable.

Table 3.3 presents pair-wise comparisons of profitability from the three investment strategies, *MAR* (p,0,6), 52*HI* (p,0,6) and *JT* (p,12,0,6) for p = 10% and 30%. The MAR strategy is significantly more profitable than the JT momentum strategy when p = 10%.

The difference is 0.24% per month with *t*-statistic of 2.45. This difference comes from both winner and loser portfolios. The return on the MAR winner portfolio is higher by 0.13% (*t*-statistic is 2.55) on average than the return on the JT winner portfolio and the return on the MAR loser portfolio is lower by 0.11 (*t*-statistic is -2.02) on average than the return on the JT loser portfolio. Also, the MAR winner portfolio tends to realize significantly higher return than the 52-week high winners, while the difference in returns between the MAR loser and the 52-week high loser portfolios is not significant. Finally, the 52-week high losers have significantly lower returns than the JT loser portfolios but the difference in returns between the 52-week high winners and the JT winners is not significant. However, when $p = 30\%$, difference in winner/loser returns or momentum profits between any pair of investment strategies is not statistically significant.

IV.C. Comparisons of Profitability from the Three Investment Strategies – Results of Fama-MacBeth Style Regressions

Although Table 3.2 shows that the winners from the three strategies significantly outperform losers for the next 6 months after the portfolios are formed, it cannot distinguish among the underlying forces driving the return continuation. It is obvious that stocks that outperformed other stocks for the previous 6 or 12 months tend to be priced close to the 52-week high and also have a higher ratio of 50-day moving average price to 200-day moving average price. In order to see the marginal effect of belonging to the winner or loser portfolio under an investment strategy while controlling for the effect of being in a winner or loser portfolio under other investment strategies, I implement a

Fama-MacBeth style cross-sectional regression analysis described in Equation (3) in Subsection III.C.

In Tables 3.3 and 3.4, I compare *JT* (30, 12, 1, 6), *52HI* (30, 1, 6), and *MAR* (30, 1, 6). Here, the JT momentum strategy has a 12-month formation period and, the holding periods for all strategies are 6 months, and there is a one-month gap between the formation period and the holding period. I use the JT momentum strategy with a 12-month formation period rather than a 6-month formation period, because the GH 52-week high and MAR strategies use much more than 6 months of historical price information when forming the portfolios. However, when I repeat this analysis with *JT* (30,6,1,6) to check for the robustness, I obtained the same results as presented here. Table 3.4 presents the time-series averages of the estimated coefficient of regression equation (3) and the differences of estimated coefficients on winner and loser dummies from the investment strategies and associated *t*-statistics as described in Subsection III.C. The second and third columns include only JT winner and JT loser dummy variables and the fourth through ninth columns include winner and loser dummies for only two of the three investment strategies. Finally, the last two columns include winner and loser dummies of all of the three investment strategies. In addition to the winner and loser dummy variables, I include one-month lagged returns and the natural logarithm of the market capitalization in order to control for the market microstructure effects and size effect. In addition, I separately present time-series averages and *t*-statistics of the coefficient estimates for all months and for non-Januarys (Panel A) and for only Januarys (Panel B). The sample period is from 1964 to 2004. In Table 3.4, price and size screening are applied, while in Table 3.5 all stocks are included.

The second and third columns of Panel A of Table 3.4 show that JT winner and loser dummies are significant when GH 52-week high or MAR strategies are not controlled for regardless of whether or not I include Januarys in the holding periods. When Januarys are included in the holding periods, the estimate of the JT winner dummy is 0.27% per month (*t*-statistic of 2.46) and that of the JT loser dummy is -0.32% per month (*t*-statistic of -3.42). This means that if a stock belongs to the JT winner portfolio, the stock's return for the 6-month holding period starting one month after the portfolio is formed is on average 0.27% higher than those of stocks that would belong to the middle portfolio if firm sizes and one-month lagged returns are identical. Similarly, stocks that are in the JT loser portfolio underperform by 0.32% per month compared to average stocks that are in middle portfolio for the holding period. The difference between the coefficients of JT winner and loser dummies is 0.60% per month with a *t*-statistic of 4.09. This means that *JT* (30,12,1,6) would produce 0.60% of monthly profits on average if stocks in the winner and loser portfolios had identical one-month lagged returns and sizes. The magnitude and statistical significance of the JT momentum profits increase when Januarys are excluded from the holding period. These results are not surprising given results of Table 3.2.

In the fourth and fifth columns, GH 52-week high winner and loser dummies are included in addition to JT momentum winner and loser dummies. The bottom part of the fourth and fifth columns shows that even though the difference in coefficient estimates between

JT winner and loser dummy is still significantly positive for all months and non-Januarys, the magnitude and statistical significance are reduced from those in the second and third columns. Monthly profit from the pure JT momentum strategy is 0.32% (*t*-statistic is 2.14) when January is included in the holding period and 0.39% (*t*-statistic is 2.53) for non-Januarys while monthly profits from a pure 52-week high strategy is 0.55% (*t*-statistic is 3.54) for all months and 0.72% (*t*-statistic is 4.69) for non-Januarys. The pure JT momentum strategy in the fourth and fifth columns would be a JT momentum strategy that includes only pairs of stocks, one of which belongs to the JT winner portfolio and the other of which belongs to the JT loser portfolio and both of which are identical in one-month lagged return, size, and membership in any other investment strategies. The dominance of the pure 52-week high strategy against the pure JT momentum strategy is consistent with the findings of George and Hwang (2004).

Reduction in profitability of the JT momentum strategy mainly comes from the decrease in magnitude of the coefficient estimate of the JT momentum loser dummy. For example, the coefficient estimate of the JT loser dummy becomes an insignificant -0.06% (*t*-statistic of -1.13) for all months while the coefficient estimate of the JT winner dummy is slightly lower (2.25% with *t*-statistic of 2.29) than that in the second column. This implies that if a stock belongs to the JT loser portfolio, the stock underperforms by only 0.06% per month for the holding period compared to stocks that are belong to the JT middle portfolio and that are identical in one-month lagged return, size, and membership in the GH 52-week high strategy. When Januarys are excluded, the coefficient of the JT loser dummy is still significantly negative, but the magnitude is significantly reduced from that in the third column (-0.12% with *t*-statistic of -2.05). This implies that a large portion of the poor performance of JT loser portfolio can be attributed to the fact that the JT loser portfolio includes many stocks that belong to the GH 52-week high loser portfolio. The coefficient estimates for the 52-week high loser dummy are significantly negative for all months and non-Januarys. However, either for all months and non-Januarys, the coefficient estimates of the JT winner dummy do not decrease significantly from those in the second and third columns. This implies that the performance of JT winner portfolio cannot be explained by the fact that the JT winner portfolio includes many stocks that also belong to 52-week high winner portfolio. The coefficient estimates of the 52-week high winner dummy are 0.06% (*t*-statistic is 1.04) and 0.11% (*t*-statistic is 2.07) for all months and non-Januarys, respectively. These results along with a significant negative coefficient on the 52-week high loser dummy suggest that profits from the pure 52-week high strategy are asymmetric; more profits come from poor performance of the loser portfolios.

The new findings of this paper are in the sixth through 11th columns where the winner and loser dummies of the moving-average ratio (MAR) strategy play significant roles even after controlling for the JT momentum and GH 52-week high strategies. Furthermore, profits from the pure MAR strategy are more statistically significant than those from the pure JT momentum or the pure GH 52-week high strategies. In the sixth and seventh columns where the regression equation includes winner and loser dummies from the JT momentum and MAR strategies, monthly profit from the pure MAR strategy is 0.58% (*t*-statistic is 6.23) for all months and 0.65% (*t*-statistic is 7.03) for non-Januarys and profit from the pure JT momentum strategy are reduced significantly from those in the second and fourth columns. However, the monthly profit from the pure JT momentum strategy is still significantly positive; 0.23% (*t*-statistic is 2.01) for all months and 0.36% (*t*-statistic is 3.04) for non-Januarys. These, along with results in third and fourth columns, suggest that neither the nearness to 52-week high price nor the ratio of the 50-day MA to the 200-day moving MA can completely explain the JT momentum profits.

Unlike the fourth and fifth columns, the reduction in the profits of the JT momentum strategy comes from decreases in the magnitude of the coefficient estimates of both winner and loser dummies for the JT momentum strategy. The coefficient estimates for the JT winner dummy decrease to 0.10% (*t*-statistic is 1.17) and 0.13% (*t*-statistic is 1.43) from 0.27% and 0.30% for all months and non-Januarys, when the winner and loser dummies from the MAR strategy are included in regression equation. Also, the coefficient estimates of the JT loser dummies decrease in magnitude to -0.13% (*t*-statistic is -1.84) and -0.23% (*t*-statistic is -3.17) from -0.32% and -0.45%. In the eighth and ninth columns, I compare the profitability of the 52-week high and MAR strategies. Neither the 52-week high nor MAR strategy dominates the other, and profits from both strategies are similar; 0.47% (*t*-statistic is 3.01) and 0.48% (*t*-statistic is 3.65) for all months and 0.68% (4.41) and 0.50 (3.62) for non-Januarys for the pure GH 52-week high and pure MAR strategies.

Finally, the tenth and 11th columns include winner and loser dummies from all three of the investment strategies. In this case, the pure JT momentum strategy does not produce statistically significant profits when Januarys are included in the holding periods at conventional significance levels (90% significance level); the monthly profit is only 0.13% with a *t*-statistic of 1.12. When Januarys are excluded, the monthly profit is marginally significant at the 90% significance level; monthly profit is 0.21 with *t*-statistic of 1.75. This suggests that a large portion of the predictive power of past returns for future returns comes from either nearness to the 52-week high price or the moving average ratio. These results confirm George and Hwang's (2004) argument that a theory in which price level relative to an anchor plays a role is more descriptive of the data than existing theories that focus on price changes based on overconfidence, conservatism, or slow diffusion of information. The tenth and 11th columns also show that the pure GH 52-week high and MAR strategies generate statistically significant profits at 99% significance level whether or not Januarys are included in the holding period. This suggests that the predictive power of nearness to the 52-week high price and the moving average ratio for future returns are distinct and that investors regard the moving averages as their anchor as well as the 52-week high.

Panel B of Table 3.4 presents the same information as Panel A except that holding periods are restricted to only Januarys in Panel B. The sixth column shows that the pure 52-week high strategy contributes most to the return reversals in Januarys (-1.42% with *t*-statistic of -2.28) and the pure MAR strategy negatively contributes to the return reversals in Januarys (0.47% with *t*-statistic of 1.42) even though the profits are not statistically significant. Average monthly profit from the pure JT momentum strategy is negative and marginally significant at 90% significance level; -0.75% with *t*-statistic of -1.71. The negative profit from the pure JT momentum strategy is asymmetric as consistent with the tax-loss selling argument. Only the coefficient estimate on the JT loser dummy is statistically significant (0.59 with *t*-statistic of 3.16), while the coefficient estimate on the JT winner dummy is insignificant (-0.16 with *t*-statistic of -0.52). The positive coefficient on the JT loser dummy in January is consistent with a tax-loss selling argument where investors tend to sell stocks with high unrealized losses at the end of year more than they would sell without tax motivation and in early January, prices of such stocks return to the fundamental values resulting in abnormal returns on the stocks. However, a more significant loss in January from the pure 52-week high strategy cannot be explained by the tax-loss selling argument. The negative profit from the pure 52-week high strategy is symmetric. These results can be explained by the window dressing argument. At the end of the calendar year, which seems to precede an important reporting date, managers in investment companies may want to include more stocks whose current prices are close to the 52-week high and less stocks whose current prices are far below the 52-week high in order to simply make their portfolios look attractive to investors. Reduction of such temporary buying or selling pressure in the beginning of the subsequent year may lead to return reversals in Januarys.

Coefficient estimates of the one-month lagged returns in Panels A show that the monthly return reversals are significant for both Januarys and non-Januarys even when I exclude from the sample all stocks that are priced less than \$5 and all stocks with market capitalizations that would place them in the smallest NYSE decile. The time-series averages of the coefficient estimates of R_{it-1} are significantly negative. This suggests that the price and size screening cannot eliminate the market microstructure effects such as bid-ask bounce or thin-trading or the possibility that the short-term return reversals may come from other sources than the market microstructure effects. Comparison of coefficient estimates of size variables from Panels A and B also confirms previous literature in which the size effects are most significant in Januarys. Without Januarys, all size coefficients are statistically insignificant. This means that there is no size effect in non-Januarys among stocks that are priced above $5 and whose market capitalizations are above NYSE smallest decile cutoff.

In order to see whether the results in Table 3.4 are primarily driven by the fact that I exclude small and low priced stocks, I repeat the same analyses as in Table 3.4 without price or size screening. Table 3.5 shows the results of the regression analyses when I include all NYSE, AMEX, and NASDAQ stocks in the sample. The results are qualitatively the same as Table 3.4. The fifth column of Table 3.5 shows that the average monthly profit from the pure JT momentum is even lower (0.04% with *t*-statistic of 0.34) than the corresponding profit in Table 3.4 while the average monthly profits from the pure 52-week high and the MAR strategy are higher than in Table 3.4. This suggests that even when I include small and low priced stocks, the past returns do not explain return continuation if I include Januarys in the holding period. As in Table 3.4, when I exclude Januarys from the holding period, the average month profit from the pure JT momentum strategy is marginally significant at 90% significant level while the average monthly profits from the pure 52-week high and MAR strategies are significantly positive.

Relative to the results in Table 3.4, the coefficients of one-month lagged returns and size are much larger in magnitude in Table 3.5. For example, for all months the coefficient estimate on R_{it-1} is -6.29 (*t*-statistic is -15.81) when I include all stocks in the sample, while it is -3.79 (*t*-statistic is -8.69) when I exclude small or low priced stocks from the sample. This suggests that small or illiquid stocks are more subject to short-term (one-month) return reversals consistent with the argument that the short-term return reversals are caused by market microstructure effects such as bid-ask bounce or liquidity effects. Also, coefficients on the natural logarithm of market capitalization are negative and statistically significant regardless of whether I include Januarys in the holding period in Table 3.5. These along with the results in Table 3.4 suggest that the size effect in non-Januarys comes from only small or low priced stocks.

IV.D. Long-Term Reversals

As introduced in Section II, George and Hwang (2004) argue that intermediate-term momentum and long-term reversals are largely separate phenomena since the intermediate-term momentum mainly comes from an anchoring bias in which investors regard the 52-week high price as their reference for estimating the current stock price, but the long-term reversals are not related to the 52-week high price. George and Hwang also argue that these findings present a challenge to existing behavioral theories that model the intermediate-term momentum and long-term reversals as integrated components of the market's responses to news. Tables 3.5 and 3.6 confirm George and Hwang's argument. In Table 3.6, I estimate regression Equation (3) in the same way as Table 3.4 except that there is 12-, 24-, 36-, or 48-month gap between portfolio formation periods and holding periods in Table 3.6. If intermediate-term return continuation and long-term return reversals are linked to each other as suggested by BSV, DHS, and HS, the investment strategy that contributes most to the intermediate-term return continuation should contribute most to the long-term return reversals. Given the results in Tables 3.3 and 3.4, where the pure 52-week high and pure MAR strategies contribute most and the pure JT momentum strategy contribute least to the intermediate-term momentum, the long-term return reversals should mainly come from the pure 52-week high or pure MAR strategy if the intermediate-term return continuation is linked to long-term return reversals.

However, Table 3.6 shows that long-term reversals mainly come from the pure JT momentum strategy. When there is a 12- or 24-month gap between the portfolio formation period and holding period, the average monthly profit from the pure JT momentum strategy is significantly negative regardless of whether Januarys are included in the holding periods. Also, when I allow a 48-month gap between the formation period and the holding period, the average monthly profit from the pure JT momentum strategy is significantly negative when I exclude Januarys from the holding periods. In any case, neither the 52-week high nor the MAR strategy produces significantly negative profits. Coupled with the results in Tables 3.3 and 3.4, this suggests that intermediate-term momentum profits mainly come from an anchoring bias where investors regard 52-week high price and moving averages as their reference for estimating current prices, but the anchoring bias is not related to long-term reversals. I repeat the analyses in Table 3.7 without price or size screening. Table 3.7 shows that return reversals from JT momentum strategy is more significant, but 52-week high or MAR strategy does not contribute on long-term return reversals even when I include all stocks in the sample. The results in Tables 3.5 and 3.6 confirm George and Hwang that intermediate-term momentum and long-term reversals are separate phenomena.

V. Conclusions and Implications for Future Research

The ratio of the 50-day moving average to the 200-day moving average seems to explain most of the intermediate-term momentum first documented by Jegadeesh and Titman (1993) together with the ratio of the current price to the 52-week high. This suggests that an anchoring bias to the 52-week high or moving averages in estimating the current stock price is more likely to be the driving force of the intermediate-term momentum than investors' conservatism (Barberis, Shleifer and Vishny, 1998) or overconfidence (Daniel, Hirshleifer, and Subrahmanyam, 1998) or slow diffusion of information (Hong and Stein, 1999). Also the predictive ability of the moving average ratio for future returns is distinct from and as significant as the ratio of current price to the 52-week high. This suggests that investors regard moving average prices as their reference prices as well as the 52-week high, while it is unclear whether there are some irrational investors who regard the moving averages and the 52-week high as their reference prices or there are two separate groups of investors where one group regards the moving averages and the other group regards the 52-week high as their reference prices. Finally, I show that neither the pure 52-week high nor the MAR strategy produces significantly negative profits when there is a more than 12-month gap between the portfolio formation period and the holding period, while there are long-term return reversals from the pure JT momentum strategy. This suggests that intermediate-term return continuation and long-term return reversals are separate phenomena and that separate theories for long-term reversals should be developed.

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Appendix 2

Table 3.1 Summary Statistics

At the beginning of each month, returns over the past six and twelve months, the ratios of the current price to the 52-week high (52-week high ratio), and the ratios of the 50-day moving average to the 200-day moving average (*MAR*) are calculated for all stocks traded on the NYSE, AMEX, and NASDAQ over the period from January 1964 to December 2004. Panel A presents the time-series averages of the cross-sectional averages and standard deviations of the returns and ratios. In Panel B, time-series averages of the estimates of the pair-wise correlation coefficients between two variables are reported.

I exclude stocks priced below $5 and stocks with market capitalizations that would place them in the smallest NYSE decile.

Panel A: Mean and Standard Deviation

	6-month return	12-month return	52-week high ratio	*MAR*
Mean	6.64%	12.92%	0.82	1.03
Standard Deviation	24.34%	35.01%	0.14	0.13

Panel B: Correlation Coefficient

	12-month return	52-week high ratio	*MAR*
6-month return	0.72	0.65	0.89
12-month return		0.62	0.78
52-week high ratio			0.59

Table 3.2 Profits from Three Investment Strategies

Average monthly returns on winner and loser portfolios and average monthly profits (with associated *t*-statistics) from three investment strategies are presented. The three investment strategies, *JT*(*p*, *J*, *D*, *K*), *52HI*(*p*, *D*, *K*), and *MAR*(*p*, *D*, *K*) are defined in Definitions 1, 2, and 4, respectively. For example, at the beginning of each month *t*, *JT*(*p*, *J*, *D*, *K*) sorts all stocks in the sample based on the buy-and-hold returns for the *J* months from *t*-*D*-*J* to *t*-*D*-1, buys equally the top *p*% of stocks (winners) and sells equally the bottom *p*% of stocks (losers), and holds this position for the next *K* months. This strategy is the same as in Jegadeesh and Titman (1993) where there is a *D*-month gap between formation and holding period. *52HI*(*p*, *D*, *K*) is defined similarly to *JT*(*p*, *J*, *D*, *K*) except that stocks are sorted by the ratio of current price to the 52-week high price instead of past returns. *MAR*(*p*, *D*, *K*) is the same as *52HI*(*p*, *D*, *K*) except that stocks are sorted by the ratio of the 50-day moving average to the 200-day moving average. I include all stocks traded on the NYSE, AMEX and NASDAQ, but exclude all stocks priced below $5 at the end of the formation period and all stocks with market capitalizations that would place them in the smallest NYSE decile. The sample period is from January 1964 to December 2004.

Panel A presents the results when I include Januarys in the holding period, Panel B shows the results for only Januarys and Panel C contains results for only non-Januarys.

Panel A: All Months

	P = 10%				*P* = 30%			
	JT(10,12,0,6)	*JT*(10,6,0,6)	*52HI*(10,0,6)	*MAR*(10,0,6)	*JT*(30,12,0,6)	*JT*(30,6,0,6)	*52HI*(30,0,6)	*MAR*(30,0,6)
1/64 – 12/04								
Winner	1.68	1.72	1.43	1.81	1.51	1.48	1.39	1.54
Loser	0.47	0.49	0.28	0.36	0.79	0.82	0.73	0.75
Winner – Loser	1.21	1.23	1.15	1.45	0.72	0.66	0.66	0.80
	(4.94)	(5.16)	(4.39)	(6.02)	(4.34)	(4.27)	(3.79)	(5.03)
1/64 – 12/83								
Winner	1.78	1.72	1.43	1.81	1.56	1.50	1.37	1.55
Loser	0.55	0.62	0.43	0.48	0.84	0.90	0.87	0.82
Winner – Loser	1.23	1.10	1.00	1.33	0.72	0.60	0.50	0.73
	(3.83)	(3.82)	(3.37)	(4.46)	(3.21)	(2.98)	(2.44)	(3.44)
1/84 – 12/04								
Winner	1.59	1.72	1.43	1.82	1.47	1.47	1.42	1.54
Loser	0.39	0.36	0.14	0.25	0.74	0.74	0.60	0.67
Winner – Loser	1.20	1.35	1.29	1.57	0.73	0.72	0.81	0.87
	(3.23)	(3.60)	(3.03)	(4.17)	(2.96)	(3.08)	(2.92)	(3.68)

Table 3.2 Continued

Panel B: January Only

	P = 10%				P = 30%			
	JT(10,12,0,6)	*JT*(10,6,0,6)	*52HI*(10,0,6)	*MAR*(10,0,6)	*JT*(30,12,0,6)	*JT*(30,6,0,6)	*52HI*(30,0,6)	*MAR*(30,0,6)
1/64 – 12/04								
Winner	3.42	3.53	2.13	3.60	3.23	3.23	2.48	3.26
Loser	5.57	5.33	5.97	5.32	4.64	4.61	5.15	4.60
Winner – Loser	-2.15	-1.80	-3.84	-1.72	-1.42	-1.38	-2.67	-1.34
	(-2.07)	(-1.42)	(-2.68)	(-1.40)	(-2.04)	(-1.78)	(-2.99)	(-1.73)
1/64 – 12/83								
Winner	3.53	3.64	2.49	3.70	3.66	3.69	2.94	3.65
Loser	6.14	5.77	6.39	5.65	5.37	5.28	5.95	5.26
Winner – Loser	-2.61	-2.13	-3.89	-1.95	-1.70	-1.59	-3.00	-1.61
	(-1.65)	(-1.41)	(-2.27)	(-1.31)	(-1.52)	(-1.52)	(-2.56)	(-1.52)
1/84 – 12/04								
Winner	3.32	3.43	1.79	3.50	2.81	2.79	2.05	2.89
Loser	5.03	4.92	5.57	5.00	3.95	3.97	4.39	3.97
Winner – Loser	-1.71	-1.49	-3.79	-1.49	-1.14	-1.19	-2.34	-1.07
	(-1.24)	(-0.73)	(-1.63)	(-0.76)	(-1.33)	(-1.01)	(-1.72)	(-0.94)

Table 3.2 Continued

Panel C: January Excluded

	P = 10%				P = 30%			
	JT(10,12,0,6)	*JT*(10,6,0,6)	*52HI*(10,0,6)	*MAR*(10,0,6)	*JT*(30,12,0,6)	*JT*(30,6,0,6)	*52HI*(30,0,6)	*MAR*(30,0,6)
1/64 – 12/04								
Winner	1.52	1.55	1.37	1.65	1.35	1.32	1.29	1.39
Loser	0.01	0.05	-0.23	-0.09	0.44	0.48	0.33	0.39
Winner – Loser	1.52	1.50	1.60	1.74	0.92	0.85	0.97	0.99
	(6.17)	(6.57)	(6.57)	(7.43)	(5.47)	(5.61)	(5.82)	(6.38)
1/64 – 12/83								
Winner	1.62	1.55	1.34	1.64	1.37	1.30	1.23	1.36
Loser	0.04	0.15	-0.11	0.01	0.42	0.50	0.40	0.42
Winner – Loser	1.58	1.39	1.44	1.63	0.94	0.80	0.82	0.94
	(5.10)	(5.05)	(5.43)	(5.64)	(4.31)	(4.12)	(4.45)	(4.58)
1/84 – 12/04								
Winner	1.43	1.56	1.40	1.67	1.34	1.35	1.36	1.41
Loser	-0.03	-0.05	-0.35	-0.18	0.45	0.45	0.26	0.37
Winner – Loser	1.46	1.61	1.75	1.85	0.89	0.90	1.10	1.04
	(3.84)	(4.45)	(4.34)	(5.04)	(3.53)	(3.88)	(4.05)	(4.48)

Table 3.3 Pair-Wise Comparisons of Profitability from Three Investment Strategies

This table presents pair-wise comparisons of profitability from the three investment strategies, *MAR* (p,0,6), *JT* (p,12,0,6) and 52*HI* (p,0,6). For each month t, I calculate returns on winner and loser portfolios and momentum profits from the three investment strategies for p = 10% and 30%. Then, the differences in returns of winner and loser portfolios and momentum profits from each pair of investment strategies are obtained. This table presents the time-series averages and t-statistics (in parentheses) of the differences. I include all stocks traded on the NYSE, AMEX and NASDAQ, but exclude all stocks priced below $5 at the end of the formation period and all stocks with market capitalizations that would place them in the smallest NYSE decile. The sample period is from January 1964 to December 2004. The numbers in bold font mean that statistical significance in 90% significance level.

		MAR – JT	***MAR – 52HI***	**52*HI – JT***
P = 10%	Winner	**0.13**	**0.38**	-0.25
		(2.55)	**(2.57)**	(-1.48)
	Loser	**-0.11**	0.08	**-0.19**
		(-2.02)	(1.23)	**(-2.24)**
	Winner-loser	**0.24**	0.30	-0.06
		(2.45)	(1.49)	(-0.26)
P = 30%	Winner	0.03	0.15	-0.12
		(0.97)	(1.77)	(-1.20)
	Loser	-0.04	0.01	-0.06
		(-1.25)	(0.25)	(-0.82)
	Winner-loser	0.07	0.14	-0.06
		(1.14)	(0.97)	(-0.37)

Table 3.4 Comparisons of JT, 52-Week High, and Moving-Average-Ratio (with Price and Size Screening)

The basic functional form of the regression equation is

$$R_{it} = b_{0kt} + b_{1kt} R_{it-1} + b_{2kt} \ln(size_{it-1}) + b_{3kt} JH_{it-D-k} + b_{4kt} JL_{it-D-k} + b_{5kt} FHH_{it-D-k} + b_{6kt} FHL_{it-D-k} + b_{7kt} MAH_{it-D-k} + b_{8kt} MAL_{it-D-k} + e_{it} ,$$

for k = 1, …, 6, and D=1, where R_{it} and $R_{it\text{-}1}$ are stock i's returns for month t and t-1, ln($size_{it\text{-}1}$) is the natural logarithm of stock i's market capitalization at the end of month t-1, $JH_{it\text{-}k}$ is a dummy variable that equals one if stock i's past performance over the 12-month period (t-D-k-11, t-D-k-1) is in the top 30% when measured by the JT momentum strategy performance criterion, and is zero otherwise; $JL_{it\text{-}k}$ equals one if stock i's past performance over the same period is in the bottom 30% as measured by the *JT* momentum strategy performance criterion, and is zero otherwise. The dummy variables, $FHH_{it\text{-}k}$, $FHL_{it\text{-}k}$, $MAH_{it\text{-}k}$, and $MAL_{it\text{-}k}$ are similarly defined except that $FHH_{it\text{-}k}$ and $FHL_{it\text{-}k}$ use the GH 52-week high strategy criterion and $MAH_{it\text{-}k}$ and $MAL_{it\text{-}k}$ use the moving-average ratio strategy criterion.

For each month, I estimate the regression equations for k=1,…, 6, and calculate the averages of the coefficient estimates. This table presents time-series averages and associated t-statistics of the averages. Also, in the bottom part of each panel, the time-series averages of differences in the coefficient estimates between winner and loser dummies from the investment strategies are presented. For example, the numbers in the row titled "JT winner dummy – JT loser dummy" means time-series average of the difference between the coefficient estimates on the JT winner and loser dummies.

Panel A presents results when Januarys are included in the holding period and when Januarys are excluded from the holding period. In Panel B, results are presented for only Januarys. Columns under the title "*JT*" include only JT momentum strategy dummies, columns under the title "*JT-52HI*" include only JT momentum and GH 52-week high strategy dummies, and so on. The same price and size screening as in Table 1 is applied to the sample data and the sample period is same as in Table 1. Numbers in bold font mean statistical significance at 90% significance level.

Table 3.4 Continued

Panel A: All months or January Excluded

	JT		*JT–52HI*		*JT-MAR*		*52HI-MAR*		*JT-52HI-MAR*	
	All Months	Jan. Excluded	All Months	Jan. Excluded	All Months	Jan. Excluded	All Months	Jan. Excluded	All Months	Jan. Excluded
Intercept	**1.79**	0.55	**2.08**	**0.91**	**1.87**	0.66	**2.07**	**0.91**	**2.05**	**0.89**
	(3.40)	(1.13)	**(4.19)**	**(1.97)**	**(3.67)**	(1.40)	**(4.17)**	**(1.96)**	**(4.19)**	**(1.96)**
R_{it-1}	**-3.47**	**-2.80**	**-3.69**	**-3.02**	**-3.62**	**-2.95**	**-3.66**	**-2.99**	**-3.79**	**-3.11**
	(-7.46)	**(-6.03)**	**(-8.32)**	**(-6.82)**	**(-8.04)**	**(-6.56)**	**(-8.15)**	**(-6.66)**	**(-8.69)**	**(-7.17)**
ln(size)	-0.05	0.03	**-0.07**	0.01	-0.05	0.03	**-0.07**	0.01	**-0.07**	0.01
	(-1.46)	(1.11)	**(-2.12)**	(0.33)	(-1.64)	(0.91)	**(-2.11)**	(0.34)	**(-2.10)**	(0.37)
JT winner dummy	**0.27**	**0.30**	**0.25**	**0.27**	0.10	0.13			0.12	**0.15**
	(2.46)	**(2.61)**	**(2.29)**	**(2.34)**	(1.17)	(1.43)			(1.47)	**(1.72)**
JT loser dummy	**-0.32**	**-0.45**	-0.06	**-0.12**	**-0.13**	**-0.23**			-0.01	-0.06
	(-3.42)	**(-4.81)**	(-1.13)	**(-2.05)**	**(-1.84)**	**(-3.17)**			(-0.18)	(-1.21)
52-week high winner dummy			0.06	**0.11**			0.05	**0.12**	0.03	0.08
			(1.04)	**(2.07)**			(1.01)	**(2.40)**	(0.49)	(1.46)
52-week high loser dummy			**-0.49**	**-0.61**			**-0.42**	**-0.56**	**-0.40**	**-0.52**
			(-4.55)	**(-5.67)**			**(-3.73)**	**(-5.00)**	**(-3.91)**	**(-4.97)**
MV ratio winner dummy					**0.26**	**0.25**	**0.30**	**0.30**	**0.25**	**0.23**
					(4.04)	**(3.81)**	**(2.97)**	**(2.78)**	**(3.74)**	**(3.34)**
MV ratio loser dummy					**-0.33**	**-0.39**	**-0.18**	**-0.20**	**-0.17**	**-0.18**
					(-4.73)	**(-5.87)**	**(-3.84)**	**(-4.26)**	**(-4.19)**	**(-4.41)**
JT winner dummy –	**0.60**	**0.76**	**0.32**	**0.39**	**0.23**	**0.36**			0.13	**0.21**
JT loser dummy	**(4.09)**	**(5.10)**	**(2.14)**	**(2.53)**	**(2.01)**	**(3.04)**			(1.12)	**(1.75)**
52-week high winner dummy –			**0.55**	**0.72**			**0.47**	**0.68**	**0.43**	**0.60**
52-week high loser dummy			**(3.54)**	**(4.69)**			**(3.01)**	**(4.41)**	**(2.86)**	**(3.94)**
MV ratio winner dummy –					**0.58**	**0.65**	**0.48**	**0.50**	**0.41**	**0.41**
MV ratio loser dummy					**(6.23)**	**(7.03)**	**(3.65)**	**(3.62)**	**(4.68)**	**(4.45)**

Table 3.4 Continued
Panel A: January Only

	JT	*JT–52HI*	*JT-MAR*	*52HI-MAR*	*JT-52HI-MAR*
Intercept	**15.47**	**14.90**	**15.14**	**14.87**	**14.78**
	(6.21)	**(6.50)**	**(6.33)**	**(6.46)**	**(6.47)**
R_{it-1}	**-10.86**	**-11.08**	**-10.99**	**-11.04**	**-11.22**
	(-5.66)	**(-6.16)**	**(-5.98)**	**(-6.08)**	**(-6.33)**
ln(size)	**-0.98**	**-0.93**	**-0.96**	**-0.93**	**-0.92**
	(-5.99)	**(-6.17)**	**(-6.07)**	**(-6.13)**	**(-6.12)**
JT winner dummy	-0.05	0.05	-0.19		-0.16
	(-0.14)	(0.14)	(-0.54)		(-0.52)
JT loser dummy	**1.11**	**0.53**	**0.96**		**0.59**
	(2.79)	**(2.63)**	**(3.48)**		**(3.16)**
52-week high winner dummy		**-0.55**		**-0.71**	**-0.56**
		(-2.21)		**(-2.80)**	**(-2.33)**
52-week high loser dummy		**0.84**		**1.16**	**0.86**
		(1.77)		**(2.48)**	**(2.07)**
MV ratio winner dummy			0.30	0.35	**0.41**
			(1.33)	(1.07)	**(1.91)**
MV ratio loser dummy			0.38	0.08	-0.05
			(1.03)	(0.42)	(-0.29)
JT winner dummy –	**-1.17**	-0.48	**-1.14**		**-0.75**
JT loser dummy	**(-2.06)**	(-0.92)	**(-2.42)**		**(-1.71)**
52-week high winner dummy –		**-1.39**		**-1.87**	**-1.42**
52-week high loser dummy		**(-2.03)**		**(-2.71)**	**(-2.28)**
MV ratio winner dummy –			-0.08	0.26	0.47
MV ratio loser dummy			(-0.17)	(0.60)	(1.42)

Table 3.5 Comparisons of JT, 52-Week High, and Moving-Average-Ratio Strategies (without Price and Size Screening)

All procedures are same as in Table 2 except that there is no price or size screening in the sample.

	JT			*JT-52HI-MAR*		
	All Months	Jan. Excl.	Jan. Only	All Months	Jan. Excl.	Jan. Only
Intercept	**3.75**	**1.92**	**23.96**	**4.08**	**2.44**	**22.09**
	(6.58)	**(3.81)**	**(10.19)**	**(7.91)**	**(5.33)**	**(10.67)**
R_{it-1}	**-6.07**	**-5.09**	**-16.80**	**-6.29**	**-5.34**	**-16.76**
	(-14.46)	**(-14.01)**	**(-6.62)**	**(-15.81)**	**(15.47)**	**(-7.09)**
ln(size)	**-0.21**	**-0.08**	**-1.64**	**-0.24**	**-0.13**	**-1.50**
	(-5.15)	**(-2.23)**	**(-9.68)**	**(-6.32)**	**(-3.67)**	**(-9.68)**
JT winner dummy	**0.26**	**0.29**	-0.05	0.08	0.09	-0.11
	(2.63)	**(2.82)**	(-0.12)	(1.05)	(1.25)	(-0.37)
JT loser dummy	**-0.32**	**-0.64**	**3.26**	0.04	**-0.10**	**1.59**
	(-2.42)	**(-5.29)**	**(5.38)**	(0.69)	**(-1.82)**	**(6.76)**
52-week high winner dummy				**0.15**	**0.23**	**-0.69**
				(2.21)	**(3.24)**	**(-2.55)**
52-week high loser dummy				**-0.34**	**-0.61**	**2.55**
				(-2.82)	**(-5.30)**	**(4.37)**
MV ratio winner dummy				**0.24**	**0.21**	**0.56**
				(3.80)	**(3.19)**	**(2.67)**
MV ratio loser dummy				**-0.24**	**-0.30**	0.38
				(-4.99)	**(-6.52)**	(1.40)
JT winner dummy –	**0.58**	**0.93**	**-3.31**	0.04	**0.19**	**-1.70**
JT loser dummy	**(3.55)**	**(5.95)**	**(-4.83)**	(0.34)	**(1.81)**	**(-4.33)**
52-week high winner dummy –				**0.50**	**0.84**	**-3.24**
52-week high loser dummy				**(2.76)**	**(4.79)**	**(-4.13)**
MA ratio winner dummy –				**0.48**	**0.51**	0.17
MA ratio loser dummy				**(5.63)**	**(5.83)**	(0.48)

Table 3.6 Long-Term Reversals (with Price and Size Screening)

All procedures and sample are same as Table 2 except that *D* = 12, 24, 36, and 48, and that sample period is from June 1968 to December 2004.

	D = 12		*D* = 24		*D* = 36		*D* = 48	
	All Months	Jan. Excl.	All Months	Jan. Excl.	All Months	Jan. Excl.	All Months	Jan. Excl.
Intercept	0.85	-0.71	**1.56**	-0.31	**2.12**	0.18	**2.37**	0.43
	(1.40)	(-1.32)	**(2.40)**	(-0.56)	**(3.17)**	(0.32)	**(3.56)**	(0.77)
R_{it-1}	**-4.86**	**-3.99**	**-5.20**	**-4.25**	**-5.32**	**-4.34**	**-5.56**	**-4.62**
	(-9.68)	**(-8.42)**	**(-10.47)**	**(-9.06)**	**(-10.74)**	**(-9.30)**	**(-11.40)**	**(-9.96)**
ln(size)	0.03	**0.14**	-0.02	**0.11**	-0.07	**0.07**	**-0.08**	0.05
	(0.67)	**(3.85)**	(-0.56)	**(2.90)**	(-1.46)	**(1.85)**	**(-1.85)**	(1.41)
JT winner dummy	**-0.17**	**-0.19**	-0.11	**-0.14**	-0.01	-0.05	-0.05	-0.09
	(-2.48)	**(-2.67)**	(-1.68)	**(-2.17)**	(-0.09)	(-0.79)	(-0.78)	(-1.48)
JT loser dummy	**0.16**	**0.12**	0.07	0.06	-0.01	-0.01	-0.05	0.05
	(4.09)	**(3.07)**	(1.80)	(1.57)	(-0.46)	(-0.30)	(1.86)	(1.70)
52-week high winner dummy	0.01	0.05	-0.03	0.01	-0.03	0.00	-0.07	-0.06
	(0.20)	(0.94)	(-0.68)	(0.21)	(-0.70)	(-0.08)	(-1.72)	(-1.28)
52-week high loser dummy	-0.03	-0.17	0.07	-0.06	0.07	-0.03	-0.01	-0.08
	(-0.32)	(-1.74)	(0.73)	(-0.59)	(0.74)	(-0.35)	(-0.14)	(-0.90)
MV ratio winner dummy	-0.07	-0.04	-0.02	-0.04	-0.01	-0.04	0.03	-0.01
	(-1.18)	(-1.46)	(-0.34)	(-0.67)	(-0.22)	(-0.79)	(0.47)	(-0.14)
MV ratio loser dummy	-0.01	-0.04	-0.01	-0.03	-0.02	-0.01	-0.01	-0.00
	(-0.38)	(-1.46)	(-0.28)	(-1.23)	(-0.22)	(-0.43)	(-0.23)	(-0.14)
JT winner dummy –	**-0.33**	**-0.31**	**-0.18**	**-0.20**	0.01	-0.04	-0.10	**-0.14**
JT loser dummy	**(-3.68)**	**(-3.42)**	**(-2.24)**	**(-2.37)**	(0.12)	(-0.51)	(-1.39)	**(-1.90)**
52-week high winner dummy –	0.04	0.22	-0.10	0.07	-0.10	0.03	-0.06	0.02
52-week high loser dummy	(0.29)	(1.53)	(-0.75)	(0.49)	(-0.77)	(0.23)	(-0.51)	(0.17)
MV ratio winner dummy –	-0.06	-0.04	-0.01	-0.01	0.00	-0.03	0.03	-0.00
MV ratio loser dummy	(-0.84)	(-0.59)	(-0.20)	(-0.16)	(0.07)	(-0.52)	(0.47)	(-0.06)

Table 3.7 Long-Term Reversals (without Price and Size Screening)

All procedures and sample are same as in Table 4 except that there is no price or size screening.

	D = 12		*D* = 24		*D* = 36		*D* = 48	
	All Months	Jan. Excl.	All Months	Jan. Excl.	All Months	Jan. Excl.	All Months	Jan. Excl.
Intercept	**2.72**	**0.96**	**2.75**	**0.88**	**2.87**	**0.95**	**2.92**	**0.98**
	(4.88)	**(2.00)**	**(4.72)**	**(1.78)**	**(4.81)**	**(1.91)**	**(4.88)**	**(1.96)**
R_{it-1}	**-6.44**	**-5.43**	**-6.52**	**-5.47**	**-6.52**	**-5.47**	**-6.49**	**-5.46**
	(-14.49)	**(-14.46)**	**(-14.55)**	**(-14.40)**	**(-14.62)**	**(-14.20)**	**(-14.46)**	**(-13.85)**
ln(size)	**-0.12**	0.00	**-0.12**	0.01	**-0.13**	0.01	**-0.13**	0.01
	(-3.01)	(0.07)	**(-2.91)**	(0.28)	**(-3.06)**	(0.14)	**(-3.09)**	(0.16)
JT winner dummy	**-0.20**	**-0.22**	-0.11	**-0.13**	-0.05	-0.09	-0.09	**-0.14**
	(-3.33)	**(-3.60)**	(-1.95)	**(-2.33)**	(-0.83)	(-1.58)	(-1.80)	**(-2.64)**
JT loser dummy	**0.15**	0.06	**0.09**	0.03	-0.00	-0.01	**0.08**	**0.08**
	(3.46)	(1.50)	**(2.16)**	(0.81)	(-0.10)	(-0.33)	**(2.71)**	**(2.61)**
52-week high winner dummy	0.05	0.13	-0.01	0.06	0.01	0.06	-0.01	0.02
	(0.67)	(1.79)	(-0.17)	(0.94)	(0.08)	(0.90)	(-0.25)	(0.36)
52-week high loser dummy	0.07	-0.16	0.05	-0.12	0.03	-0.12	-0.07	**-0.20**
	(0.59)	(-1.45)	(0.46)	(-1.10)	(0.33)	(-1.15)	(-0.74)	**(-2.26)**
MV ratio winner dummy	-0.09	**-0.12**	-0.05	-0.08	-0.03	-0.08	-0.00	-0.05
	(-1.63)	**(-1.99)**	(-0.93)	(-1.46)	(-0.70)	(-1.46)	(-0.04)	(-0.96)
MV ratio loser dummy	0.00	-0.04	0.01	-0.02	-0.01	-0.01	0.03	**0.04**
	(0.12)	(-1.23)	(0.42)	(-0.64)	(-0.27)	(-0.55)	(1.35)	**(1.82)**
JT winner dummy –	**-0.35**	**-0.28**	**-0.19**	**-0.17**	-0.04	-0.08	**-0.17**	**-0.21**
JT loser dummy	**(-4.55)**	**(-3.70)**	**(-2.79)**	**(-2.33)**	(-0.67)	(-1.19)	**(-2.95)**	**(-3.68)**
52-week high winner dummy –	-0.02	0.29	-0.06	0.18	-0.03	0.18	0.05	0.23
52-week high loser dummy	(-0.12)	(1.66)	(-0.37)	(1.09)	(-0.19)	(1.12)	(0.39)	(1.58)
MV ratio winner dummy –	-0.10	-0.08	-0.06	-0.07	-0.03	-0.06	-0.03	-0.10
MV ratio loser dummy	(-1.57)	(-1.30)	(-1.02)	(-1.08)	(-0.52)	(-1.10)	(-0.54)	(-1.52)

Vita

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