R^2 and Price Inefficiency*

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Abstract

Motivated by the recent debate on return R^2 as an information-efficiency measure, this paper proposes and examines a new hypothesis that R^2 is related to investors' biases in processing information. We provide a model to show that R^2 decreases with the degree of the marginal investor's overreaction to firm-specific information. This theoretical result motivates an empirical hypothesis that stocks with lower R^2 should exhibit more pronounced overreaction-driven price momentum. Empirically, we confirm that such a negative relationship between R^2 and price momentum exists, and find this relationship robust to controls for risk as well as several alternative mechanisms, such as slow information diffusion, information uncertainty, fundamental R^2 and illiquidity. Furthermore, we also document stronger long-run price reversals for stocks with lower R^2. Taken together, our results suggest that return R^2 could be related to price inefficiency.

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1 Introduction

A firm's "return R^2" is the R^2 statistic derived from regressing an individual stock's returns either on a single market index or on multiple common factors. Roll (1988) initially finds that individual stocks' return R^2 is low for U.S. firms, indicating high firm-specific return variations. More recently, Morck, Yeung, and Yu (2000) show that return R^2 is also low among other developed economy stock markets, while high among emerging markets, even after controlling for fundamental R^2. They find that differences in public investor property rights explain the cross-country differences in return R^2. They argue that stronger public investor property rights promote trading on firm-specific information, thus generating higher firm-specific return variations and lower R^2. Furthermore, Durnev, et al. (2003) show that, among U.S. stocks, return R^2 is negatively correlated with measures of stock price informativeness about future earnings. Taken together, these studies conclude that lower R^2 is caused by greater capitalization of firm-specific information, and can thus be used as a measure of information efficiency of stock prices.

This R^2-based efficiency measure has gained increasing popularity and is used in various empirical studies of corporate investment and emerging market development. For example, several recent studies, e.g., Wurgler, (2000), Durnev, Morck, and Yeung (2004), and Chen, Goldstein, and Jiang (2006), find that the capital investment of firms and countries with lower return R^2 is more sensitive to fluctuation in their stock prices. Using the information-efficiency interpretation of return R^2, these authors interpret their findings as evidence in favor of firm managers learning useful information from stock prices about firm fundamentals and incorporating this information into their investment decisions.

However, this information-efficiency interpretation of return R^2 remains controversial. On the empirical side, several studies, e.g., Chan and Hameed (2006), Kelly (2005), Ashbaugh-Skaife, Gassen, and LaFond (2006), Griffin, Kelly, and Nadari (2006), and Yang and Zhang (2006), find no consistent relationship between return R^2 and measures of stock price informativeness using both U.S. and international data. On the

theoretical side, several authors, e.g., West (1988), Campbell, et al. (2001), and Peng and Xiong (2006), also point out that the information-efficiency interpretation of return R^2 is difficult to reconcile with standard models, in which investors react rationally to information.

Facing this debate, this paper proposes and examines a new hypothesis that return R^2 is related to investors' biases in processing information and the resulting price inefficiency. In particular, we provide a theoretical model to examine investor overreaction as a determinant of return R^2, and then empirically test the model's implications. We analyze a risky asset, whose payoff is determined by two unobservable factors - a market factor and a firm-specific factor. We focus on a marginal investor's learning processes about these two factors and the resulting stock price dynamics. On the one hand, our model demonstrates that, if the investor rationally reacts to information, a greater amount of information does not decrease return R^2.[1] On the other, we show that the investor's overreaction to firm-specific information affects return R^2. This overreaction increases the stock's firm-specific return variance and reduces its return R^2. Therefore, our model derives the result that the stock's return R^2 decreases with the degree of the marginal investor's overreaction.[2] While the recent debate on return R^2 has been largely focused on measures of information efficiency, the role of investors' behavioral biases is unexplored. We intend to fill this gap by empirically examining the effect of investor overreaction on return R^2.

Since it is difficult to directly measure the degree of the marginal investor's overreaction, we focus on the relationship between return R^2 and price momentum, a direct outcome of investor overreaction, as suggested by DeLong, et al. (1990) and Daniel,

[1]The basic intuition is that information only shifts the timing of uncertainty resolution, it does not affect the total amount of uncertainty resolution over time. More firm-specific information helps the investor to resolve more uncertainty about the firm fundamentals in the earlier period, as a result the stock price also fluctuates more in this period. However, there will be less firm-specific uncertainty left for the later period, and therefore less stock price fluctuation in the second period. Overall, the amount of firm-specific information does not increase the average return variance across the two periods and therefore does not decrease the stock's return R^2.

[2]Note that by analyzing the marginal investor's overreaction, our model implicitly assumes that rational arbitrageurs do not fully eliminate the price effects of irrational investors. We interpret the marginal investor's overreaction as a joint outcome of some irrational investors' overreaction to information and limited arbitrage by other rational investors.

Hirshleifer and Subrahmanyam (1998). Price momentum is a phenomenon initially documented by Jegadeesh and Titman (1993) where a simple strategy based on buying winners in the prior 6 months and shorting losers in the same period can generate economically and statistically significant trading profits over the following 1 to 6 months. In particular, we examine two empirical hypotheses. The first hypothesis posits that stocks with lower return R^2 exhibit more pronounced price momentum. This hypothesis is the focal point of our empirical analysis. To further confirm that the relationship between return R^2 and price momentum is driven by investor overreaction, we also examine a second hypothesis that stocks with lower return R^2 have stronger long-run price reversals.

To examine the first hypothesis, we sort all NYSE/AMEX/NASDAQ stocks into quintiles based on their return R^2 and compare the magnitude of price momentum profits across different R^2 quintiles. We find that the relationship between return R^2 and price momentum profits is negative and significant. A momentum strategy of buying recent winners and selling recent losers generates a significant value-weighted profit of 181 basis points per month in the lowest R^2 quintile, and the profit monotonically decreases to an insignificant 51 basis points per month in the highest R^2 quintile. This negative relationship between R^2 and momentum profits remains robust after controlling for alternative R^2 measures, sorting procedures, and return adjustments.

We also examine the long-run performance of the R^2-sorted momentum portfolios for various holding periods. We find that the momentum profits for all five R^2 quintiles dissipate after two years, indicating price reversals in the long-run. Furthermore, the magnitude of the price reversals tends to be stronger among the lower-R^2 quintiles and weaker among the higher-R^2 quintiles, results consistent with our second hypothesis.

In addtion, we use Fama-MacBeth (1973) cross-sectional regressions to examine these hypotheses at the individual stock level. We find that the regression coefficient on the interaction term of return R^2 with the past year's return is significantly negative, while the coefficient on the interaction term of return R^2 with the past five years' return is significantly positive. These results further confirm that both price momentum and long-run reversal effects become more pronounced as return R^2 decreases.

To account for systematic risk factors, we adjust stock returns by employing the Fama and French (1993) three-factor model at the portfolio level and, following Daniel, Grinblatt, Titman, and Wermers (1997), by employing a characteristic-based matching procedure which accounts for return premia associated with size and book-to-market characteristics at the individual stock level. In both cases, we find our results to be robust.

The goal of our empirical analysis is to examine whether return R^2 is related to price inefficiency, which is ultimately a joint outcome of some irrational investors' biased reaction to information and limited arbitrage by other rational investors. Although arbitrage cost could contribute to our finding that lower R^2 stocks tend to have more pronounced price momentum and reversal patterns, it is important to recognize that, without investor biases, arbitrage cost alone cannot generate these patterns in the first place.

We also recognize that several alternative mechanisms could potentially affect the relationship between R^2 and momentum. To control for these alternative effects, we construct residual R^2 measures by regressing a stock's return R^2 on a series of control variables and reexamine the relation between the residual R^2 measures and price momentum. To account for the slow-information-diffusion effect suggested by Hong and Stein (1999), we add firm size and analyst coverage, the two variables employed by Hong, Lim, and Stein (2000), as well as institutional ownership, to our list of control variables. To control for the information uncertainty effect suggested by Jiang, Lee, and Zhang (2005) and Zhang (2006), we incorporate return volatility and dispersion of analyst forecasts as control variables. We also include a stock's fundamental R^2 from regressing the stock's earnings on aggregated market- and industry-earnings as an additional control variable. Finally, to adjust for illiquidity and other market imperfections, we add share turnover and an illiquidity measure proposed by Amihud (2002) as control variables. The information uncertainty and the illiquidity variables also proxy for arbitrage cost. Even after employing these control variables, we still find a negative and monotonic relationship between the residual R^2 measures and momentum profits, suggesting that the negative relationship between return R^2 and price

momentum is not driven by these alternative effects.

Our study contributes to the debate on the use of return R^2 as an information-efficiency measure. While several other studies (e.g., Chan and Hameed, 2006, Kelly, 2005, Ashbaugh-Skaife, Gassen, and LaFond, 2006, Griffin, Kelly, and Nadari, 2006, and Yang and Zhang, 2006) also challenge this use, we propose and test a new hypothesis of return R^2 based on a formal model. Our analysis that R^2 is related to price inefficiency can help understand the above findings. In particular, Kelly (2005) and Chan and Hameed (2006) show that stocks with lower R^2 tend to be smaller, have lower institutional ownership, analyst coverage and liquidity, signs inconsistent with the argument that lower R^2 corresponds to higher information efficiency. Their finding is, however, consistent with our framework in the sense that these stocks tend to have a larger retail investor clientele, which is more likely to display overreaction.

Given our finding that return R^2 is related to price inefficiency, one has to interpret the earlier empirical findings based on return R^2 as a information-efficiency measure with great caution. Previously documented properties of low R^2 stocks could be caused by investor overreaction, instead of firm-specific information. For example, the aforementioned finding that the capital investment of firms and countries with lower return R^2 is more sensitive to fluctuation in their stock prices (e.g., Wurgler, 2000, Durnev, Morck, and Yeung, 2004, and Chen, Goldstein, and Jiang, 2006) could suggest that firm managers react to investor frenzy or sentiment, instead of value-relevant information in stock prices.

Our study differs from those papers that examine firms' fundamental R^2. Jin and Myers (2006) show that the lack of transparency affects risk sharing between insiders and outsiders, and therefore fundamental R^2. Irvine and Pontiff (2005) show that product market competition increases firm-specific fundamental cash flow volatilities. We take fundamental R^2 as given and focus on how return R^2 can deviate from fundamental R^2 due to investors' overreaction to information. Our finding also corroborates with a recent study by Bradt, Brav and Graham (2005), who show that idiosyncratic volatility is associated with the speculative trading of retail investors.

Our paper is organized as follows. Section **??** uses a theoretical model to lay out

our empirical hypotheses, while section 3 describes the data and variable construction. We study the cross-sectional relationship between return R^2 and price momentum, as well as reversals, in Section 4. We provide further discussions and conclude in Section 5.

2 Theory and Empirical Hypotheses

In this section, we first provide a simple model to highlight investors' overreaction to firm specific information as a determinant of return R^2. We then introduce two empirical hypotheses relating R^2 to price momentum and reversals.

Our model has two periods and three dates: $t = 0, 1, 2$. There is a risky stock, which generates a final payoff at $t = 2$. The final payoff is unobservable before $t = 2$, and is determined by a linear combination of two random factors:

$$f = \beta u + v \tag{1}$$

where u is a market factor and v is a firm-specific factor. β is the stock's factor loading on the market factor. The fundamental factors, u and v, are independent and both have a Gaussian distribution. More specifically, we assume that on date 0, investors' prior beliefs about these two factors are

$$u \sim N(0, 1/\tau_u), \quad v \sim N(0, 1/\tau_v).$$

Without any loss of generality, we assume that both variables have a zero mean. τ_u and τ_v are the respective inverses of the variables' variances. Thus, $1/\tau_u$ and $1/\tau_v$ represent the initial uncertainty in the market and firm-specific factors respectively.

Since investors cannot observe the two fundamental factors until date 2, on date 1 they have to rely on their learning processes. We analyze the learning processes of a marginal investor in the market. The marginal investor observes two signals about the two fundamental factors:

$$\begin{aligned} s_u &= u + \epsilon_u, \\ s_v &= v + \epsilon_v. \end{aligned}$$

s_u is a noisy signal about the market factor. It contains a noise component ϵ_u, which is independent of u and v, and has a Gaussian distribution with a zero mean and a variance of $1/\tau_{s,u}$. s_v is a noisy signal about the firm-specific factor. It contains a noise component ϵ_v, which is independent of u, v, and ϵ_u, and has a Gaussian distribution with a zero mean and a variance of $1/\tau_{s,v}$. The parameters $\tau_{s,u}$ and $\tau_{s,v}$ capture the precision of the two signals.

We consider the possibility that the marginal investor may overreact to information. It is well documented in the psychology literature that individuals, when updating their beliefs, tend to give new information more weight than implied by Bayes' rule (Kahneman and Tversky, 1982). Psychological evidence also shows that the overreaction bias is particularly severe in those faced with diffuse tasks that require judgments but provide only noisy and delayed feedback (see Einhorn, 1980). Fundamental valuation of financial securities is a good example of this type of task. Evidence of the overreaction bias has also been found in professional security analysts and economic forecasters (for a review, see DeBondt and Thaler, 1995).

To incorporate investor overreaction, we assume that the marginal investor overestimates the precision of the signal s_v about the firm-specific factor by a multiple of ϕ, where $\phi \geq 1$. If $\phi = 1$, the investor correctly reacts to the signal. If $\phi > 1$, the investor overreacts. This approach of modelling investor overreaction is consistent with Daniel, Hirshleifer and Subrahmanyam (1998) and others, in which an agent overestimate his information precision.

It is important to note that, in the financial market, the behavior of the marginal investor is jointly determined by the interaction between irrational and rational investors. As suggested by Shleifer and Vishny (1997), as long as rational investors are risk averse or subject to capital constraints, they would be unable to fully eliminate price inefficiencies created by irrational investors. In equilibrium, this interaction is reflected in the degree of the marginal investor's overreaction parameter ϕ, which increases with the irrational investors' behavioral biases and decreases with the rational investors' arbitrage effectiveness. For example, ϕ would be higher for a stock with a larger fraction of (potentially irrational) retail investors or, equivalently, one with a

smaller fraction of (rational) institutional investors. ϕ could also be higher for illiquid stocks which tend to have a higher arbitrage cost.

We assume that the marginal investor correctly perceives the precision of the signal s_u about the market factor. Because the market factor is closely watched by all market participants, there is a more effective arbitrage force for incorporating market information than there is for firm-specific information. Thus, we choose to focus on the effect of irrational investor's overreaction to firm-specific information.

Bayes rule implies that the marginal investor's posterior beliefs about the two fundamental factors are Gaussian, and that the means of the beliefs are determined by

$$\begin{aligned} E(u|s_u) &= \frac{\tau_{s,u}}{\tau_u + \tau_{s,u}} s_u, \\ E(v|s_v) &= \frac{\phi\tau_{s,v}}{\tau_v + \phi\tau_{s,v}} s_v. \end{aligned}$$

Note that the marginal investor's reaction coefficient to s_v, $\frac{\phi\tau_{s,v}}{\tau_v+\phi\tau_{s,v}}$, increases with the investor's overreaction parameter ϕ.

The marginal investor's learning processes determine stock price dynamics. For simplicity, we assume that the interest rate is zero and that the marginal investor is risk neutral.[3] This setup allows us to derive the stock price on each of the three dates:

$$\begin{aligned} p_0 &= 0, \\ p_1 &= \beta E(u|s_u) + E(v|s_v) = \beta \frac{\tau_{s,u}}{\tau_u + \tau_{s,u}} s_u + \frac{\phi\tau_{s,v}}{\tau_v + \phi\tau_{s,v}} s_v, \\ p_2 &= \beta u + v. \end{aligned}$$

We are interested in the composition of the average return variance over the two model periods, and in particular, in the contribution of the market versus the firm-

[3]Incorporating risk aversion would introduce a risk premium into prices, but would not affect the general characterization of information-related price fluctuations.

specific variance components. The average return variance is derived as follows:

$$\begin{aligned}\Sigma &\equiv \frac{1}{2}[Var(p_1 - p_0) + Var(p_2 - p_1)] \\ &= \frac{\beta^2}{2\tau_u} + \underbrace{\frac{1}{2\tau_v} + \frac{\phi(\phi-1)\tau_{s,v}}{(\tau_v + \phi\tau_{s,v})^2}}_{\Sigma_v}. \end{aligned} \tag{2}$$

This average return variance corresponds to the stationary level of return variance in a dynamic setting (e.g., Peng and Xiong, 2006), and is consistent with the empirical measures of R^2 that use long sample periods.

There are two components in Σ. The first component, $\beta^2/(2\tau_u)$, represents the return variance related to the market factor, and is equal to half of the stock's fundamental market-factor uncertainty. The second component, Σ_v, represents the return variance related to the firm-specific factor. Σ_v equals half of the stock's firm-specific fundamental uncertainty, $1/(2\tau_v)$, plus a second term related to the marginal investor's overreaction. When the investor is fully rational ($\phi = 1$), Σ_v is only determined by the firm-specific fundamental uncertainty; when the investor overreacts ($\phi > 1$), it is easy to show that Σ_v increases with ϕ, the degree of investor overreaction.[4]

The empirical measure of return R^2 is often extracted by regressing a firm's stock returns onto the market return and other common factors. This regression R^2 corresponds to the fraction of a firm's return variance that can be explained by the market factor in our model:

$$R^2 \equiv \frac{\frac{\beta^2}{2\tau_u}}{\frac{\beta^2}{2\tau_u} + \Sigma_v} = \frac{\frac{\beta^2}{\tau_u}}{\frac{\beta^2}{\tau_u} + \frac{1}{\tau_v} + \frac{2\phi(\phi-1)\tau_{s,v}}{(\tau_v+\phi\tau_{s,v})^2}}. \tag{3}$$

This formula allows us to discuss the effects of information and investor overreaction on return R^2.

We first discuss the case in which the marginal investor is rational. By substituting $\phi = 1$ into equation (**??**), one sees directly that the return R^2 is equal to $\frac{\beta^2/\tau_u}{\beta^2/\tau_u + 1/\tau_v}$,

[4] Also note that, if $\phi < 1$, the investor underreacts to the firm-specific information, causing Σ to be less than the average fundamental uncertainty. However, this situation is inconsistent with the well documented excess volatility of stock returns (see, for example, Shiller, 1981).

the fundamental R^2. Simple as it seems, this result highlights an often ignored point – in an equilibrium with only rational investors, more firm-specific information does not decrease return R^2. The basic intuition is that information only shifts the timing of uncertainty resolution, it does not affect the total amount of uncertainty resolution over time. It is easy to see this intuition in our model: more firm-specific information on date 1 helps investors to resolve more uncertainty in v, therefore the stock price p_1 is more informative about v and it fluctuates more from date 0 to date 1. However, there will be less firm-specific uncertainty left for the later period from date 1 to date 2, and therefore less price fluctuation in the second period. In fact, the average firm-specific return variance per period is simply half of the total firm-specific fundamental uncertainty, as in equation (**??**). Therefore, when the marginal investor is rational, the amount of firm-specific information does not affect the average firm-specific return variance and the return R^2. We summarize these observations in the following proposition:

Proposition 1. *If the marginal investor is rational ($\phi = 1$), a stock's return R^2 is independent of the amount of firm-specific information incorporated into its price.*

It is useful to note that if we only consider the price dynamics in the first period and ignore the dynamics in the following period, then more firm-specific information would lead to a higher firm-specific return variance and a lower return R^2. However, such an analysis does not match the usual empirical measures of return R^2, which typically employs stock returns over long periods of time. Proposition 1 shows that after taking account of the uncertainty resolution process over the full horizon in our model, more firm-specific information does not decrease return R^2. This result directly highlights the concerns raised by West (1988), Campbell, et al. (2001), and Peng and Xiong (2006) on using return R^2 as an information-efficiency measure.

We will now discuss the effect of investor overreaction on return R^2. By calculating the first order derivative of equation (**??**) with respect to ϕ, we can verify that the return R^2 decreases with the degree of the marginal investor's overreaction to firm-specific information. This is because investor overreaction increases firm-specific return variance and therefore reduces return R^2. We formalize this result in the following

proposition:

Proposition 2. *If the marginal investor overreacts to firm-specific information, the stock's return R^2 decreases with ϕ, the degree of investor overreaction.*

Proposition 2 shows that investors' overreaction to information could be an important determinant of firms' return R^2. While the literature has put great effort into examining the relationship between return R^2 and price informativeness, the role of investors' biased reactions to information has been largely ignored. Could the cross-sectional variation in the degree of investor overreaction help explain the difference in return R^2? We will examine this question in our empirical analysis.

It is difficult to directly measure the degree of investors' overreaction to information. Instead, we choose to examine the link between return R^2 and other price dynamics that are direct outcomes of investor overreaction. Several studies, e.g., DeLong, et al. (1990) and Daniel, Hirshleifer, and Subrahmanyam (1998), show that investor overreaction can lead to medium-term price momentum. In the model of DeLong, et al., traders with extrapolative expectations overreact to past stock returns; while in the model of Daniel, Hirshleifer, and Subrahmanyam, overconfident investors overreact even more to their private information after a positive prior return confirming their information. Furthermore, Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) find evidence that price momentum tends to be reversed in the long run, confirming that at least a sizable portion of price momentum is generated by investor overreaction. One could divide the first period in our model into two sub-periods and incorporate either the mechanism of DeLong, et al. or that of Daniel, Hirshleifer, and Subrahmanyam.[5]

[5]More specifically, consider adding another date, 1A, immediately after date 1. If we incorporate the investor's over-extrapolation of the prior return on date 1, following the mechanism described by DeLong, et al. (1990), then the stock price change between dates 1 and 1A would follow the same direction as that between dates 0 and 1, thus generating price momentum between dates 0 and 1A. We could also adopt the setting of Daniel, Hirshleifer, and Subrahmanyam (1998): On date 1, the investor overreacts to certain information; on date 1A, new information is released, and self-attribution bias causes the investor to further overreact to his information on date 1. In this setting, the stock price change between dates 1 and 1A is also positively correlated with that between dates 0 and 1, again creating price momentum between dates 0 and 1A. In both settings, the price overreaction between dates 0 and 1A will be eventually corrected when the liquidation value of the stock is revealed on date 2, thus creating a price reversal between dates 1A and 2.

Then, there will be overreaction-driven price momentum in the first period and this overreaction will be eventually corrected in the second period.

Motivated by these studies, we propose the following hypothesis:

Hypothesis 1. *All else equal, stocks with lower return R^2 exhibit more pronounced medium-term price momentum.*

Hypothesis 1 is the focal point of our empirical analysis. In addition, we control for risk and several other possible mechanisms, such as those related to slow information diffusion, information uncertainty, fundamental R^2 and market illiquidity, by employing a series of control variables. To further confirm that return R^2 is related to investor overreaction, we also expect lower R^2 stocks to exhibit stronger long-run price reversals, as summarized in the following hypothesis:

Hypothesis 2. *All else equal, stocks with lower return R^2 show stronger long-run price reversals.*

3 Data Description

3.1 Data and Sample Selection

Our sample includes all NYSE/AMEX/NASDAQ listed securities on the Center for Research in Security Prices (CRSP) data files with sharecodes 10 or 11 (we exclude ADRs, closed-end funds, REITs) from July 1963 to December 2002. We require firms to have information on a number of balance sheet and income statement items from the COMPUSTAT database. To ensure that the accounting variables are known before the period during which stock returns are measured, we match CRSP stock returns from July of year t to June of year t+1 with accounting variables for the fiscal year ending in year t-1.

We obtain the following variables from COMPUSTAT with the data item numbers in parentheses. Book equity is defined as stockholder's equity (216) (or common equity (60) plus preferred stock par value (130), or asset (6) minus liabilities (181)), minus preferred stock (liquidating value (10), or redemption value (56), or par value (130)),

plus balance sheet deferred taxes and investment tax credit (35), if available, minus post retirement asset (330), if available. Earnings are earnings before interest, which is income before extraordinary items (18) plus interest expense (15) plus income statement deferred taxes (50), when available. Asset is total asset (6). Firm size (*Size*) is measured by multiplying the CRSP number of shares outstanding by share price at the end of June of year t. BE/ME is calculated by dividing book equity by market capitalization as measured at the end of year t-1.

We also employ analyst coverage and institutional ownership data from the Institutional Brokers Estimate System (IBES) and the Standard & Poors, respectively. Analyst coverage (*Num Analyst*) is defined as the monthly number of analysts providing current fiscal year earnings estimates, averaged over the previous year. This data is available from 1976 onwards. Institutional ownership (*Inst*) is measured in December of the year t-1 and is available from 1980 onwards.

To measure information uncertainty surrounding a stock, we compute its total return volatility (*Tvol*) and analyst dispersion (*Disp*). Total return volatility is the standard deviation of a stock's weekly returns over the previous year. Analyst dispersion is the monthly standard deviation of analysts' annual earnings forecasts divided by the absolute value of the mean forecast, averaged over the previous year, as in Diether, Malloy, and Scherbina (2002).

Finally, as additional controls, we employ monthly share turnover (*Turnover*), defined as the monthly number of traded shares divided by shares outstanding, averaged over the previous year, and Amihud's (2002) illiquidity measure (*Illiq*), which is the average daily absolute return divided by daily dollar trading volume over the previous year. Both variables are available over the entire sample period from 1963 to 2002.

3.2 Construction of Return R^2

We use weekly returns to measure each stock's return R^2. The weekly frequency is a compromise between lower estimation precision at monthly frequencies and more confounding microstructure effects such as nonsynchronous trading and bid-ask bounce at daily frequencies. We define weekly returns as compounded daily returns from Wednes-

day close to the following Wednesday close (e.g., Hou, 2006, and Hou and Moskowitz, 2005). R^2 measures constructed from these weekly returns are then matched with monthly returns to test our empirical hypotheses.

More specifically, we follow Roll (1988), Durnev, *et al.* (2003) and Durnev, *et al.* (2004) in estimating a regression of each stock's weekly returns on the contemporaneous returns of the market portfolio as well as on the French 48 industry portfolio to which the stock belongs:

$$r_{i,t} = \alpha_{i,t} + \beta_i r_{m,t} + \gamma_i r_{I,t} + \epsilon_{i,t} \tag{4}$$

where $r_{i,t}$ is the return of stock i, and $r_{m,t}$ and $r_{I,t}$ are returns of the value-weighted CRSP market portfolio and industry portfolio in week t. We require a minimum of 20 observations in estimating return R^2. We exclude stock i when calculating both the market return and the industry return. For example, the industry return is computed by

$$r_{I,t} \equiv \frac{\sum_{j \in I, j \neq i} w_{j,t}\ r_{j,t}}{\sum_{j \in I, j \neq i} w_{j,t}}$$

where $w_{j,t}$ is the market capitalization of stock j in industry I. Excluding stock i when calculating $r_{I,t}$ prevents potential spurious correlations between $r_{i,t}$ and $r_{I,t}$. The regression R^2 from equation (**??**) is

$$R^2 \equiv 1 - \frac{\sum_t \epsilon_{i,t}^2}{\sum_t (r_{i,t} - \bar{r}_{i,t})^2}.$$

Table 1 presents the summary statistics of six R^2 measures that differ either in estimation sample period or in whether or not they adjust for degrees of freedom in estimating regression (**??**). R^2_{P1} is the R^2 estimated using weekly returns over the past one year. The mean of this variable is 0.16 and the median is 0.11, with 25% of the stocks having an R^2 value less than 0.04 and 25% of the stocks having an R^2 value greater than 0.23. R^2_{PS} is estimated using weekly returns over the entire past sample. Its mean and median are 0.12 and 0.09 respectively. R^2_{FS} is estimated using the full sample of weekly return data. Its mean and median are 0.09 and 0.06. $adj.R^2_{FS}$, $adj.R^2_{P1}$, and $adj.R^2_{PS}$ are the corresponding adjusted R^2 measures. Panel B of Table

1 presents the correlation matrix of these R^2 measures. As expected, each R^2 and its corresponding adjusted R^2 are highly correlated, with correlations ranging from 0.97 to 1. The correlations between R^2_{P1}, R^2_{PS} and R^2_{FS} are also large and statistically significant, ranging from 0.65 to 0.83.

Due to noise in individual stocks' weekly returns, the R^2 measures from regression (**??**) can be noisy, especially with limited time series data. R^2_{FS} employs the largest number of observations, and therefore should be more precise if the true R^2 is constant or is mean-reverting over time. Since the primary objective of this paper is not to construct feasible trading strategies, but to examine return R^2, we use R^2_{FS}, the full sample R^2 measure, for the majority of our analysis. We also report results based on other R^2 measures using past returns such as the one-year and the past-sample R^2 measures as robustness checks.

As a control variable in our analysis, we also employ a stock's fundamental R^2 – the variation in a stock's fundamentals that can be explained by market- and industry-wide fundamental movement. We estimate the fundamental R^2 by regressing a stock's earnings onto the earnings of the aggregate market and onto the earnings of the industry to which the stock belongs:

$$E_{i,t} = \alpha^E_{i,t} + \beta^E_i E_{m,t} + \gamma^E_i E_{I,t} + \epsilon^E_{i,t} \tag{5}$$

where $E_{i,t}$ is earnings scaled by total asset, and $E_{m,t}$ and $E_{I,t}$ are the value-weighted scaled earnings of the market portfolio and the industry portfolio (both excluding the stock itself). To improve precision, equation (**??**) is estimated over the entire sample period for each stock. The variable FRSQ is defined as the R^2 statistic from this regression.

4 Empirical Analysis

In this section, we report our empirical analysis of the relationship between return R^2 and price momentum. We first summarize the characteristics of R^2-sorted portfolios, and then analyze the patterns of medium-term price momentum and long-run price reversals across these R^2-sorted portfolios. We also use Fama-MacBeth regressions to

further study the links between R^2 and price momentum and reversals at the individual stock level. Finally, we control for several alternative mechanisms using a series of control variables.

4.1 Summary Statics of R^2 Sorted Portfolios

Each year, we first sort stocks into quintile portfolios based on their full-sample return R^2 using NYSE breakpoints, and then compute the average characteristics of each R^2 quintile. Table 2 reports the time series averages of the cross-sectional mean characteristics of R^2-sorted portfolios. This table shows that firm size, analyst coverage, and institutional ownership all increase monotonically across the R^2 quintiles: The firm size (market capitalization) increases from 84.2 million in the lowest quintile to 4.39 billion in the highest quintile, the number of analysts covering a stock increases from 2.7 to 16.9, and the percentage of institutional ownership increases from 20.1% to 51.1%.

These patterns are consistent with several recent studies of return R^2. Kelly (2005) and Chan and Hameed (2006) find that, in both U.S. and emerging markets, stocks with lower R^2 are smaller and have less analyst coverage and lower institutional ownership. As noted by these authors, these patterns in R^2 portfolio characteristics contradict the argument that stocks with lower return R^2 have more informative prices, because smaller stocks with less analyst coverage tend to have less informative prices (e.g., Atiase, 1985, Arbel and Strebel, 1982, and Collins, Kothari, Rayburn, 1987, among others). However, given that these stocks have a larger retail investor clientele who are more likely to possess behavioral biases, these patterns are consistent with our theory (Proposition 2) that return R^2 decreases with the marginal investor's degree of overreaction. There are several pieces of evidence supporting this argument. First, smaller stocks with less analyst coverage tend to be held by retail investors (e.g., Falkenstein, 1996, and Gompers and Metrick, 2001); second, retail investors are more likely to have biased reactions to information (e.g., Barber and Odean, 2000); and finally, a stock's idiosyncratic volatility, which is inversely related to return R^2, increases with retail investors' speculative trading activity (e.g., Brandt, Brav and Graham, 2005).

Table 2 also shows that fundamental R^2 increases monotonically across the return

R^2 quintiles. However, the range of fundamental R^2 (from 0.291 in the lowest R^2 quintile to 0.414 in the highest) is much smaller than the range of return R^2 (from 0.058 to 0.373), suggesting that the variation in fundamental R^2 is too small to explain the variation in return R^2. Table 2 also shows that across the return R^2 quintiles, return volatility decreases monotonically, while the dispersion in analyst forecasts tend to increase. In addition, *Illiq* decreases monotonically, while *Turnover* is smaller in the lowest R^2 quintile and is relatively flat in the other quintiles.

4.2 R^2 and Price Momentum

To explore the relationship between return R^2 and price momentum, we report in Table 3 the average monthly returns on momentum portfolios for stocks in different R^2 quintiles using a double-sorted five-by-five grid. At the beginning of each month, all stocks in our sample are first ranked by an R^2 measure using NYSE breakpoints and placed into quintile portfolios. Within each R^2 quintile, stocks are further sorted into quintiles based on past twelve month return (skipping the most recent month).[6] The value-weighted returns on these double-sorted portfolios are computed over the following month. The time series averages of the monthly portfolio returns and their t-statistics (in italics), as well as the differences in returns between momentum quintiles 5 and 1 within each R^2 quintile, are reported. For robustness, we will also report, in Section **??**, R^2-based momentum profits based on independently sorted momentum portfolios and equal-weighted portfolio returns. Throughout the paper, we follow Asness (1995), Fama and French (1996), and Grundy and Martin (2001) in focusing mainly on momentum profits with a one-month holding period, but report profits with alternative holding periods in Section **??**.

To control for the potential differences in size and BE/ME characteristics across different portfolios, we also report characteristic-adjusted returns to account for the premia associated with size and BE/ME following the characteristic-matching procedure proposed by Daniel, et al. (1997). For each month, all stocks in our sample

[6] We skip one month between the formation period and the holding period to minimize bid-ask bounce and other microstructure effects.

are first sorted into size deciles, based on NYSE breakpoints, and then within each size decile further sorted into book-to-market deciles using NYSE breakpoints. Stocks are value-weighted within each of these 100 portfolios to form a set of 100 benchmark portfolios. To calculate the size and BE/ME-hedged return for an individual stock, we subtract the return of the value-weighted benchmark portfolio, to which that stock belongs, from the return of that stock. The expected value of this excess return is zero if size and BE/ME completely describe the cross-section of expected returns.

Panel A reports average returns of portfolios sorted by each stock's full-sample R^2, R^2_{FS}, and the stock's cumulative raw return over the past year (skipping the most recent month), Ret (-12:-2). The left half of the panel presents results based on raw returns. In the lowest R^2_{FS} quintile, the average value-weighted raw return spread between past winners (momentum quintile 5) and past losers (momentum quintile 1) is 181 basis points per month with a t-statistic of 6.65. This return spread falls steadily as R^2_{FS} increases. In the highest R^2_{FS} quintile, the return spread drops to an insignificant 51 basis points per month. The differences across R^2 quintiles are highly significant: the test of the hypothesis that the average momentum profit is the same across all five R^2 quintiles produces an F-statistic of 3.40, indicating a rejection at the one-percent significance level. We also reject the null hypothesis that the momentum profit is identical across the lowest and highest quintiles with a t-statistic of 3.22. The negative and monotonic relationship between return R^2 and momentum profits demonstrated here is clearly consistent with Hypothesis 1.

The average characteristic-adjusted returns are reported in the right half of panel A. As expected, the average size and book-to-market adjusted return for each double-sorted portfolio is lower than the corresponding average raw return. However, the average spread between momentum quintiles 5 and 1 within each R^2_{FS} quintile only decreases slightly. Moreover, the pattern of the momentum spread across different R^2_{FS} quintiles remains unchanged. It decreases from a significant 152 basis points in R^2_{FS} quintile 1 to an insignificant 42 basis points in R^2_{FS} quintile 5. The F-statistic for the null of constant characteristic-adjusted momentum spread across R^2 quintiles equals 3.89 and is significant at one-percent. This result suggests that the negative

relationship between return R^2 and momentum profits is not driven by differences in size and book-to-market characteristics across portfolios.

In Panel A, we also report the intercepts and the associated t-statistics from time series regressions of raw and characteristic-adjusted momentum spreads onto the Fama and French (1993) three factor model. The model employs the excess returns on the market portfolio and returns on two factor-mimicking portfolios (SMB and HML) designed to capture the size and book-to-market effects. The intercepts from the time series regressions are slightly larger than the corresponding return spreads, and the negative relationship between R^2 and momentum profits remains unchanged. For example, even after essentially adjusting returns twice using both the characteristic benchmark model and the Fama and French (1993) three factor model, recent past winners outperform losers by 176 basis points (t-stat=7.80) in the lowest ranked R^2_{FS} quintlie, and this number monotonically decreases to 68 basis points (t-stat=2.99) for the highest R^2_{FS} quintile.

Panel B reports the average returns on portfolios sorted first by R^2_{PS}, the R^2 estimated from weekly returns over the entire past sample, and then by each stock's cumulative raw return over the past year (skipping the most recent month), Ret (-12:-2). The pattern by which the momentum profits vary across different R^2_{PS} quintiles is very similar to that of R^2_{FS}. The value-weighted return spread decreases monotonically from a significant 173 basis points per month for the lowest R^2 quintile to an insignificant 56 basis points per month for the highest. The size and book-to-market adjusted return spread also decreases monotonically from 146 basis points per month to an insignificant 39 basis points per month. Finally, the Fama-French three-factor intercepts display a similar trend across R^2_{PS} quintiles.

Panel C reports results for double-sorted portfolios based on R^2_{P1}, the R^2 estimated from weekly returns over the past year, and each stock's cumulative raw return over the past year (skipping the most recent month), Ret (-12:-2). The pattern by which momentum profits vary across R^2_{P1} quintiles is again similar to those of R^2_{FS} and R^2_{PS}. The value-weighted return spreads decrease monotonically from 140 basis points per month in the lowest R^2 quintile to 65 basis points per month in the highest. The

size and book-to-market adjusted value-weighted return spread decreases from 118 basis points per month to 42 basis points per month. As expected, the differences in momentum profits across R^2_{P1} quintiles are slightly smaller due to the measurement errors in the R^2_{P1} variable.

Overall, the results in Table 3 strongly support a negative relationship between return R^2 and price momentum profits, even after controlling for different portfolios' market risk, size and book-to-market characteristics. Such a relationship is consistent with Hypothesis 1, which posits that stocks with lower R^2 should exhibit more pronounced price momentum.

4.3 Robustness of R^2-Sorted Price Momentum

We have performed numerous additional tests and found the negative relationship between R^2 and price momentum to be robust. For brevity, only a subset of the robustness results are reported in Table 4. The rest of these results are available upon request.

Panel A of Table 4 reports results from sorting stocks using $adj.R^2_{FS}$. They are very similar to results in the previous section. There is again a negative and monotonic relationship between R^2 and momentum profits (using both raw and characteristic-adjusted returns). This negative relationship is actually slightly stronger than that associated with the unadjusted R^2_{FS}. In unreported results, we have also examined $adj.R^2_{PS}$- and $adj.R^2_{P1}$- sorted momentum profits, and found results similar to Tables 3B and 3C which employ unadjusted R^2 measures.

Panel B of Table 4 performs independent sorts using R^2_{FS} and Ret (-12:-2), instead of the sequential sorting procedure employed in the previous tests. We observe that the same negative and monotonic relationship between R^2 and momentum profits still holds with the independent-sorting procedure. We also perform the independent-sorting procedure using other R^2 measures, R^2_{PS} and R^2_{P1}, and find similar results. These results confirm that the negative relationship between R^2 and momentum profits is not sensitive to the sorting procedure used.

Panel C reports *equal-weighted* average monthly returns (both raw and characteristic-

adjusted returns) for portfolios sorted by R^2_{FS} and Ret (-12:-2). To prevent the microstructure effects that are usually associated with small, low-priced stocks from unduly influencing on the equal-weighted portfolio returns, we exclude stocks with a price less than \$5 and a market capitalization below the 10th percentile NYSE breakpoint at the beginning of the formation period.[7] Similar price and market capitalization screens are commonly imposed in the literature, e.g., Jegadeesh and Titman (2001). We find that equal-weighted momentum profit again decreases monotonically with R^2_{FS}. Similar results are obtained using other R^2 measures, and therefore are not reported.

Panel D reports value-weighted returns on portfolios double-sorted by R^2_{FS} and cumulative raw return over the past *six months* (skipping the most recent month), Ret (-6:-2). We again observe a negative and monotonic relationship between R^2 and momentum profits.

In summary, the results in Table 4 demonstrate that the negative relationship between R^2 and price momentum remains robust when we employ different R^2 measures, different stock sorting procedures, and different portfolio return specifications.

4.4 Return R^2 and Long-Run Reversals

Hypothesis 2 stipulates that, if price momentum is driven by investors' overreaction, we would expect to see reversals in the long run when prices eventually converge to their fundamental values. Table 5 (Panels A through E) reports the long-run performance of the R^2-sorted momentum portfolios for various holding periods. Panel A repeats Table 3A as the short-term performance benchmark with a formation period of the previous twelve months skipping the most recent month (month $t-12$ to month $t-2$) and a one-month holding period (month t). Panels B, C, D and E correspond to the same formation period but different holding periods of six months (month t to month $t+5$), one year (month t to month $t+11$), years 2 and 3 (month $t+12$ to month $t+35$), and years 4 and 5 (month $t+36$ to month $t+59$) after formation, respectively. In Panel F, we turn the tables and change the formation period to the past five years skipping the

[7] The microstructure effects could potentially be large, as Hong, Lim, and Stein (2000) find that the price momentum effect does not exist among small and low-priced stocks.

most recent year (month $t-60$ to month $t-13$) while keeping the holding period fixed at one month (month t). We report value-weighted average raw and characteristic-adjusted returns of the momentum portfolios and the return spreads between past winners and losers within each R^2 quintile, along with the associated t-statistics.

Panel B shows that, in the first 6 months after portfolio formation, the negative and monotonic relationship between R^2 and price profits remains. The raw momentum profit decreases from 122 basis points per month in the lowest R^2 quintile to 41 basis points per month in the highest. The size and book-to-market adjusted momentum profit follows a similar pattern, decreasing from 105 basis points per month to 37 basis points per month.

Panel C demonstrates that there is still a negative relationship between R^2 and momentum profits for the first year after portfolio formation. However, both the magnitude of momentum profits and the differences in profits across R^2 quintiles are substantially smaller. In the lowest R^2 quintile, the momentum strategy yields an average raw profit of only 66 basis points per month, and the average profit declines to an insignificant 24 basis points for the highest R^2 quintile. The size and book-to-market adjusted momentum profit exhibits a similar pattern.

Panel D reports momentum profits from one year to three years after portfolio formation. Across all R^2 quintiles, momentum strategies produce negative average return spreads (for both raw and characteristic-adjusted returns), and most of these are statistically significant. In addition, the return reversals tend to be stronger in lower R^2 quintiles than in higher R^2 quintiles.

Panel E shows that the reversal patterns in Panel D persist when we evaluate the profitability of momentum strategies over a holding period that is even further away from the formation period, i.e., from three years to five years after portfolio formation. Furthermore, the reversals are strongest in the lowest R^2 quintile and diminish gradually as R^2 increases. There is no evidence of reversals in the highest R^2 quintile.

Figure 1 plots the cumulative momentum profits for each R^2 quintile over the period from one month to five years after portfolio formation. Panel A plots cumulative raw

average profits and Panel B plots characteristic-adjusted profits. The graphs confirm the findings in Panels A-E – the momentum profits across all five R^2 quintiles reverse at longer horizons and that the reversal tends to be stronger for lower R^2 quintiles.

The evidence on the long-run performance of momentum strategies in Panels A-E and Figure 1 is consistent with the findings in the literature, e.g., Lee and Swaminathan (2000) and Jegadeesh and Titman (2001), that the momentum profits are concentrated in the first few months after portfolio formation, and that they tend to dissipate after 6 months, and eventually reverse at longer horizons. We also note that in Figure 1 the cumulative profits (raw and characteristic-adjusted) from portfolio formation to year 5 are negative for all R^2 quintiles (the characteristic-adjusted profit in quintile 4 is the only exception), indicating an "over-correction" of the medium-term momentum effect in the long run.[8] This result suggests that other factors may also contribute to the long-run reversal of momentum strategies.

In Panel F, within each R^2 quintile, we sort stocks into quintile portfolios based on their returns over the past five years skipping the most recent year (month -60 to $t-13$), and compute their value-weighted average returns for the next month (month t). This procedure allows us to study the prevalence of the DeBondt and Thaler (1985) long-run winner/loser effect for stocks with different levels of R^2. The results show that, among low R^2 stocks, a portfolio of long-run past winners underperforms past losers by 97 basis points per month, and the magnitude of the underperformance decreases to 55 basis points per month among high R^2 stocks. Therefore, low R^2 stocks not only experience a more pronounced medium-term momentum effect, but also a stronger long-run reversal effect. Insofar as the long-run reversal is related to stock market overreaction, this panel provides additional support for our hypothesis that investor overreaction drives both return R^2 and price momentum.

[8] Cooper, Gutierrez, and Hameed (2004) and Griffin, Ji, and Martin (2003) also reach similar conclusions.

4.5 Fama-MacBeth Regressions

In this subsection, we further analyze the relationship among return R^2, medium-term momentum effect and long-run reversal effect at the individual stock level using monthly Fama and MacBeth (1973) cross-sectional regressions. These regressions complement and provide further robustness checks to our portfolio sorting results. They allow us to employ individual stocks without imposing quintile breakpoints and to include a greater number of control variables for average returns. The cross-sectional regressions also provide an alternative weighting scheme to the value-weighted portfolios employed in the previous tests, thereby providing another robustness check that our portfolio results are not driven by the choice of weighting scheme used to form test portfolios.[9]

Each month from July 1968 to December 2002, we regress the cross-section of individual stock returns in excess of the one-month T-bill rate on: (1) the logarithm of market capitalization, $\ln(size)$, and the logarithm of book-to-market ratio, $\ln(BE/ME)$, to control for the average return differences related to these two stock characteristics; (2) the previous month's return, $Ret(-1:-1)$, to control for the one-month reversal effect of Jegadeesh (1990); (3) return over the previous year skipping the most recent month, $Ret(-12:-2)$, to capture the medium-term momentum effect; (4) return over the previous five years skipping the most recent year, $Ret(-60:-13)$, to capture the long-run reversal effect; and (5) a stock's R^2_{FS} after a logistic transformation, $logitR^2_{FS}$, or cross-sectional R^2_{FS} ranking.[10] Most important, we include interaction terms between the R^2 measures and past returns to study the relationship between return R^2 and the medium-term momentum and long-run reversal effects. We restrict our regression sample to stocks whose prices are above \$5 and whose market capitalization is greater than the 10th percentile NYSE breakpoint at the beginning of each month to ensure

[9] Each coefficient in the cross-sectional regressions is the return to a minimum variance arbitrage (zero-cost) portfolio, with a weighted average value of the corresponding regressor equal to one and weighted average values of all other regressors equal to zero. The weights are tilted towards smaller and more volatile stocks.

[10] We perform the logistic transformation because R^2_{FS} is bounded between zero and one. The logistic transformation helps remove the excess skewness and kurtosis of the original R^2_{FS} measure while preserving its monotonicity.

that our regression coefficients are not heavily influenced by small and illiquid stocks.

Table 6 reports the time-series averages of the cross-sectional regression coefficients and their time-series t-statistics. The first two regressions show that individual stock returns are positively related to BE/ME, past year's return and R^2_{FS}. By contrast, they are negatively related to past month's return and past five years' return, and insignificantly related to firm size. The regression coefficients of the past year's return and past five years' return are consistent with the medium-term momentum and long-run reversal effects. The third regression adds an interaction term between R^2_{FS} and the past year's return, $Ret(-12 : -2)$. The coefficient of this interaction term is negative and statistically significant, suggesting that the medium-term momentum effect is stronger among low R^2 stocks. The fourth regression replaces the interaction term between R^2_{FS} and the past year's return with one between R^2_{FS} and past five years' return, $Ret(-60 : -13)$. The regression coefficient is positive and significant, suggesting that the long-term reversal effect is also stronger among low R^2 stocks. The next regression simultaneously includes the above two interaction terms. Both coefficients are significant and maintain their appropriate signs. The regressions in the rest of Table 6 substitute a stock's R^2_{FS} with the cross-sectional quintile ranking of the stock's R^2_{FS}, and find similar results.

To summarize, our regression findings confirm the portfolio-level results that stocks with lower return R^2 not only exhibit more pronounced medium-term price momentum, but also stronger long-run reversals. These findings support Hypotheses 1 and 2 and are consistent with our theory that greater investor overreaction generates lower return R^2.

4.6 Controlling for Other Effects

The relationship between return R^2 and medium-term price momentum may also be induced by mechanisms other than investor overreaction. In this subsection, we include several variables in our analysis to control for several alternative effects.

First, a stock's return R^2 is partially determined by its fundamental correlation with the market and its industry portfolio. To control for the effect of the fundamental

correlations, we include a stock's fundamental R^2 derived from regressing its earnings on aggregated market- and industry-earnings as a control variable.

Second, the alternative mechanisms proposed in the literature for price momentum may also affect the relationship between R^2 and momentum. Hong and Stein (1999) show that, when firm-specific information diffuses slowly among heterogeneous investors and when investors fail to extract useful information from market prices, stock prices may underreact to the information and display a momentum pattern. Hong, Lim, and Stein (2000) provide supporting empirical evidence for the slow-information-diffusion effect using firm size and analyst coverage as proxies for the speed of information diffusion. To account for this effect, we employ firm size and analyst coverage as control variables in our analysis of the relationship between R^2 and price momentum. In addition, several other studies, e.g., Badrinath, Kale, and Noe (1995) and Hou (2006), suggest that institutional ownership is also related to the speed of information flow. Therefore, we include institutional ownership as a control variable as well. In addition, Jiang, Lee, and Zhang (2005) and Zhang (2006) argue that if price momentum is driven by investors' psychological biases, momentum would be more pronounced for stocks with greater information uncertainty since the investor biases are likely to be more severe for these stocks. Empirically, these studies use firm size, analyst coverage, dispersion in analyst forecasts, and total return volatility as proxies for information uncertainty. Motivated by these studies, we include dispersion in analyst forecasts and total return volatility as additional variables in our analysis to control for the effect of information uncertainty.

Finally, illiquidity and other market imperfections might also affect price momentum. Lee and Swaminathan (2000) and Hou, Peng, and Xiong (2006) find that price momentum strategy profits increase with trading volume. To account for such an effect, we include a stock's share turnover in the list of control variables. We also control for the impact of illiquidity using the measure proposed by Amihud (2002) – the average ratio of a stock's daily absolute return to the daily dollar trading volume over the prior year. The higher the Amihud measure, the less liquid a stock's shares. The information uncertainty and illiquidity variables also serve as proxies for arbitrage cost.

To control for the aforementioned effects, we construct a series of residual R^2 measures by regressing the full-sample R^2 (after a logistic transformation) on different sets of control variables, and then form momentum portfolios within different quintiles of stocks sorted by these residual R^2 measures ($ResR^2$).

The first residual R^2 measure we construct uses firm size as the only control variable, and is denoted by

$$Res.\ R^2\ (Size).$$

In the second specification, all three slow-information-diffusion proxies (firm size, analyst coverage and institutional ownership) are employed. We denote the residuals by

$$Res.\ R^2\ (Size,\ Analyst,\ Inst).$$

In the third specification, we further control for a stock's fundamental R^2, and denote the residuals by

$$Res.\ R^2\ (Size,\ Analyst,\ Inst,\ FRSQ).$$

The fourth specification adds a stocks' total return volatility. We denote the residuals by

$$Res.\ R^2\ (Size,\ Analyst,\ Inst,\ FRSQ,\ Tvol).$$

The fifth specification also includes analyst dispersion. We denote the residuals by

$$Res.\ R^2\ (Size,\ Analyst,\ Inst,\ FRSQ,\ Tvol,\ Disp).$$

Due to the limited availability of data on analyst coverage and institutional ownership, the residual R^2 measures that employ those two variables as part of the controls only cover the sample period from 1981 onwards.

In the last two specifications of residual R^2, we control for turnover and Amihud's (2002) illiquidity measure. To avoid the sample period being shortened by the availability of analyst coverage and institutional holding data, we only include firm size as the additional control variable. We denote the residuals by

$$Res.\ R^2\ (Size,\ Turnover),$$

and

$$Res.\ R^2\ (Size,\ Illiq).$$

We then form double-sorted stock portfolios using these residual R^2 measures and the past 12 month stock return (excluding the most recent month). The average monthly raw and characteristic-adjusted returns for these portfolios are reported in Table 7. Panels A through G report the results for each of the seven residual R^2 measures.

The momentum profits, either raw or characteristic-adjusted, always decrease monotonically from low to high residual R^2 quintiles, regardless of the regression specification used to estimate the residual R^2. For example, when only firm size is employed as the control variable (Panel A), past winners outperform past losers by 192 basis points per month among stocks in the lowest quintile of residual R^2, and this spread shrinks to 55 basis points for stocks in the highest quintile of residual R^2. We observe the same pattern in momentum profits when we restrict our sample to the post-1981 period, during which we can control for firm size, analyst coverage, institutional ownership, fundamental R^2, total return volatility and analyst dispersion (Panel E). The average raw momentum spread in the lowest residual R^2 quintile is 115 basis points per month, and it declines to an insignificant 21 basis points in the highest residual R^2 quintile. When we control for firm size and illiquidity (Panel G), the average raw momentum profit is 187 basis points per month in the lowest residual R^2 quintile, and it declines monotonically to 58 basis points per month in the highest. In all seven cases, we can reject the null that the average momentum profit is the same across all five residual R^2 quintiles at the one percent significance level.

In summary, Table 7 demonstrates that the negative relationship between return R^2 and price momentum is not driven by effects related to slow information diffusion, fundamental R^2, information uncertainty, turnover, or illiquidity.

5 Conclusion and Further Discussions

In this paper, we examine the determinants of individual stocks' return R^2. We first provide a theoretical model to show that when the marginal investor reacts rationally to information, a greater amount of firm-specific information does not decrease a stock's return R^2. In contrast, our model shows that, when the marginal investor overreacts to firm-specific information, a stock's return R^2 decreases with the degree of investor overreaction. Motivated by this theoretical result, we empirically analyze the relationship between return R^2 and a direct outcome of investor overreaction – price momentum.

Consistent with our theory, we find a negative relationship between return R^2 and price momentum. In the lowest R^2 quintile, a momentum strategy of buying winners over the past 12 months and selling losers over the same period generates a significant value-weighted profit of 181 basis points in the following month. This profit decreases monotonically to an insignificant 51 basis points in the highest R^2 quintile. This negative relationship between R^2 and momentum profits is robust to alternative R^2 measures, sorting procedures, risk adjustments, as well as to controlling for alternative mechanisms such as slow information diffusion, information uncertainty, fundamental R^2 and illiquidity. We also find that the momentum profits dissipate after two years, consistent with the hypothesis that they are being driven by overreaction. Furthermore, the magnitude of the reversals tends to be stronger in the lower R^2 quintiles and weaker in the higher R^2 quintiles. Individual stock-level analysis using Fama-MacBeth cross-sectional regressions also provides additional confirmation that low R^2 stocks tend to have both stronger medium-term price momentum and long-run reversals. Overall, our results support the hypothesis that a stock's return R^2 decreases with the degree of investor overreaction, and thus is related to price inefficiency.

Our finding that return R^2 is related to investor overreaction challenges the popular use of return R^2 as a price-efficiency measure. In particular, several studies find that return R^2 has explanatory power for countries' and firms' capital investment. Wurgler (2000) shows that the elasticity of investment to industry growth is higher in countries with lower average return R^2. Durnev, Morck and Yeung (2004) and Chen, Goldstein

and Jiang (2006) find that the sensitivity of U.S. firms' investment to their stock prices is negatively related to return R^2. Based on the information efficiency argument of R^2, these authors interpret their findings as evidence for firm managers learning value-relevant information from stock prices and incorporating this information into their corporate investment decisions. However, given our finding that return R^2 is negatively related to investor overreaction, the aforementioned empirical result of a negative link between return R^2 and the sensitivity of firms' investment to stock prices could suggest that, when making investment decisions, firm managers react to investor frenzy or sentiment instead of information about firm fundamentals.

Finally, our evidence that investor overreaction affects return R^2 may also help us understand the relationship between R^2 and information. In particular, according to our model, when the marginal investor overreacts to firm-specific information, equation (**??**) implies a complex relationship between return R^2 and the precision of the investor's information. This relationship is dependent on the degree of the investor's overreaction (ϕ), the precision of his information ($\tau_{s,v}$), and the precision of his prior beliefs (τ_v): If $\phi\tau_{s,v} < \tau_v$, the return R^2 decreases with the information precision; on the other hand, if $\phi\tau_{s,v} > \tau_v$, the return R^2 increases with the information precision. Although it is not the aim of this paper to reconcile the contradicting evidence discovered by the earlier studies on the relationship between return R^2 and information, our model shows that this relationship could be more complex than previously thought. Accounting for this complexity may help future studies to eventually resolve this debate.

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Table 1. Descriptive Statistics for Firms' R^2

This table presents the summary statistics and correlations for several measures of firm level R^2. R^2_{P1} is the R^2 estimated using the past one year weekly return data, and R^2_{PS} and R^2_{FS} are estimated from the entire past sample and the full sample of weekly return data, respectively. *adj.* R^2_{P1}, *adj.* R^2_{PS}, and *adj.* R^2_{FS} are the corresponding adjusted R^2 measures. ***, ** and * represent significance levels at 1%, 5% and 10% respectively.

Panel A. Summary Statistics

Variable name	Mean	Std	Skew	Kurt	Q1	Median	Q3	N
R^2_{P1}	0.16	0.15	1.36	1.57	0.04	0.11	0.23	153391
R^2_{PS}	0.12	0.11	1.21	1.36	0.04	0.09	0.18	156189
R^2_{FS}	0.09	0.10	2.01	5.93	0.02	0.06	0.13	17276
adj. R^2_{P1}	0.12	0.16	1.30	1.93	0.00	0.07	0.20	153391
adj. R^2_{PS}	0.11	0.11	0.31	13.46	0.03	0.08	0.18	156189
adj. R^2_{FS}	0.08	0.10	1.58	5.62	0.01	0.05	0.12	17276

Panel B. Pearson Correlations

	R^2_{FS}	R^2_{P1}	R^2_{PS}	*adj.* R^2_{FS}	*adj.* R^2_{P1}
R^2_{P1}	0.65 ***				
R^2_{PS}	0.83 ***	0.72 ***			
adj. R^2_{FS}	0.99 ***	0.66 ***	0.83 ***		
adj. R^2_{P1}	0.66 ***	1.00 ***	0.72 ***	0.66 ***	
adj. R^2_{PS}	0.81 ***	0.72 ***	0.97 ***	0.81 ***	0.73 ***

Table 2. Characteristics of R^2 Sorted Portfolios

This table reports the average values of several control variables across R^2_{FS} quintiles. Each year, firms are sorted into the R^2 quintiles based on NYSE breakpoints and the mean characteristics are computed within each quintile. The time series averages of the annual mean values are shown. *Mcap.* is the market capitalization of a firm, measured in millions of dollars. *Num Analyst* is the average number of analysts providing current fiscal year earnings forecasts, available from 1976 and on. *Inst* is the percentage institutional ownership, available from 1980 and on. R^2_{Fdmtl} is the fundamental R^2 of the firm, estimated using the full sample. TVOL is total volatility (standard deviation of weekly returns over the full sample period). DISP is analyst dispersion (standard deviation of analysts' annual earnings forecast divided by the absolute value of the mean forecast). TURN is monthly turnover (monthly number of shares traded divided by number of shares outstanding). ILLIQ is Amihud's (2002) illiquidity measure (average daily absolute return over daily dollar trading volume) $\times 10^5$. Firms with stock prices less than $5 are excluded.

R^2 Rank	R^2	*Mcap.* (million $)	*Num Analyst*	*Inst* (%)	R^2_{Fdmtl}	TVOL	DISP	TURN	ILLIQ ($\times 10^5$)
1	0.058	84.2	2.7	20.1	0.291	0.072	0.147	0.052	0.258
2	0.137	251.6	4.8	33.1	0.294	0.062	0.149	0.063	0.076
3	0.191	590.5	7.5	40.7	0.298	0.057	0.183	0.064	0.038
4	0.255	1572.6	11.1	48.3	0.312	0.053	0.230	0.065	0.016
5	0.373	4394.0	16.9	51.1	0.414	0.046	0.227	0.060	0.008

Table 3. R^2 and Price Momentum

Average monthly raw and characteristic-adjusted returns on portfolios sorted by various R^2 and price momentum measures are reported over the period from July, 1964 to December, 2002. At the beginning of each month, stocks are ranked by an R^2 measure using NYSE breakpoints and placed into quintiles. Within each R^2 quintile, stocks are then sorted into quintiles based on past twelve month return or past six month return (skipping the most recent month). The value-weighted raw and adjusted returns on these double-sorted portfolios are computed over the following month and their average values and t-statistics (in *italics*) as well as the differences in returns between momentum quintile 5 and 1 within each R^2 quintile are reported. The adjusted returns employ a characteristic-based matching procedure which accounts for return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Also reported are the intercepts and the corresponding t-statistics from time series regressions of the "5-1" raw and characteristic-adjusted spreads on the Fama and French (1993) 3-factor model which employs the market excess returns and returns on two factor-mimicking portfolios for the size and book-equity effects. Panel A reports results for portfolios sorted on the full-sample R^2 (R^2_{FS}) and cumulative raw return over the past year (Ret (-12:-2)). Panels B and C replace the full-sample R^2 with the R^2 estimated from weekly returns over the entire past sample (R^2_{PS}), and over the past one year (R^2_{P1}), respectively.

Panel A: Double-Sorted Quintile Portfolios of R^2_{FS} and Ret(-12:-2)

	Value-Weighted Raw Returns								Value-Weighted Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
RSQ1	-0.0067	0.0008	0.0056	0.0080	0.0114	**0.0181**	**0.0206**	RSQ1	-0.0159	-0.0094	-0.0059	-0.0041	-0.0006	**0.0152**	**0.0176**
	-1.83	*0.30*	*2.40*	*3.25*	*3.74*	*6.65*	*7.58*		*-10.65*	*-8.30*	*-6.15*	*-4.57*	*-0.55*	*6.70*	*7.80*
2	0.0023	0.0067	0.0101	0.0122	0.0156	**0.0133**	**0.0157**	2	-0.0082	-0.0039	-0.0014	0.0003	0.0037	**0.0119**	**0.0141**
	0.68	*2.44*	*4.20*	*4.92*	*5.01*	*5.14*	*6.03*		*-5.69*	*-4.34*	*-1.82*	*0.33*	*2.83*	*5.32*	*6.28*
3	0.0059	0.0091	0.0097	0.0130	0.0152	**0.0093**	**0.0121**	3	-0.0040	-0.0018	-0.0015	0.0011	0.0036	**0.0076**	**0.0104**
	1.82	*3.59*	*3.96*	*5.45*	*4.89*	*3.40*	*4.49*		*-2.91*	*-1.92*	*-2.05*	*1.26*	*2.49*	*3.32*	*4.60*
4	0.0090	0.0085	0.0088	0.0123	0.0165	**0.0075**	**0.0101**	4	-0.0014	-0.0012	-0.0020	0.0012	0.0047	**0.0062**	**0.0085**
	2.88	*3.46*	*3.87*	*5.41*	*5.69*	*2.66*	*3.61*		*-1.02*	*-1.38*	*-2.60*	*1.52*	*3.62*	*2.78*	*3.90*
RSQ5	0.0103	0.0105	0.0090	0.0122	0.0154	**0.0051**	**0.0083**	RSQ5	0.0004	0.0006	-0.0008	0.0015	0.0046	**0.0042**	**0.0068**
	3.65	*4.73*	*4.17*	*5.37*	*5.23*	*1.72*	*2.89*		*0.27*	*0.77*	*-1.24*	*2.11*	*3.14*	*1.81*	*2.99*

Panel B: Double-Sorted Quintile Portfolios of R^2_{PS} and Ret(-12:-2)

	Value-Weighted Raw Returns								Value-Weighted Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
RSQ1	-0.0017	0.0057	0.0090	0.0122	0.0155	**0.0173**	**0.0193**	RSQ1	-0.0103	-0.0042	-0.0019	0.0006	0.0043	**0.0146**	**0.0165**
	-0.46	*2.06*	*3.94*	*5.17*	*5.01*	*5.60*	*6.13*		*-6.09*	*-3.75*	*-2.03*	*0.65*	*3.16*	*5.66*	*6.25*
2	0.0029	0.0083	0.0093	0.0117	0.0169	**0.0140**	**0.0163**	2	-0.0057	-0.0012	-0.0010	0.0010	0.0053	**0.0110**	**0.0132**
	0.79	*3.05*	*4.16*	*5.10*	*5.88*	*4.69*	*5.40*		*-3.53*	*-1.18*	*-1.17*	*1.27*	*4.24*	*4.48*	*5.32*
3	0.0035	0.0069	0.0096	0.0114	0.0151	**0.0116**	**0.0133**	3	-0.0051	-0.0015	-0.0004	0.0008	0.0043	**0.0094**	**0.0112**
	0.88	*2.40*	*3.93*	*4.93*	*5.40*	*3.35*	*3.78*		*-2.42*	*-1.42*	*-0.50*	*0.92*	*3.31*	*3.28*	*3.81*
4	0.0050	0.0083	0.0084	0.0111	0.0151	**0.0101**	**0.0129**	4	-0.0036	-0.0011	-0.0012	0.0007	0.0044	**0.0080**	**0.0103**
	1.34	*3.02*	*3.59*	*4.86*	*5.44*	*3.15*	*3.97*		*-1.87*	*-1.02*	*-1.53*	*0.85*	*3.40*	*2.99*	*3.81*
RSQ5	0.0067	0.0078	0.0078	0.0095	0.0123	**0.0056**	**0.0086**	RSQ5	-0.0016	-0.0009	-0.0009	0.0001	0.0024	**0.0039**	**0.0065**
	1.73	*2.98*	*3.50*	*4.35*	*4.58*	*1.55*	*2.35*		*-0.73*	*-0.80*	*-1.17*	*0.13*	*1.88*	*1.35*	*2.23*

Panel C: Double-Sorted Quintile Portfolios of R^2_{P1} and Ret(-12:-2)

	Value-Weighted Raw Returns								Value-Weighted Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
RSQ1	0.0014	0.0074	0.0099	0.0131	0.0154	**0.0140**	**0.0160**	RSQ1	-0.0085	-0.0025	-0.0018	0.0009	0.0033	**0.0118**	**0.0126**
	0.40	*2.85*	*4.57*	*6.05*	*5.32*	*4.59*	*5.15*		*-5.65*	*-2.50*	*-2.05*	*1.05*	*2.85*	*5.45*	*5.06*
2	0.0018	0.0068	0.0079	0.0110	0.0156	**0.0138**	**0.0158**	2	-0.0078	-0.0028	-0.0023	0.0004	0.0044	**0.0122**	**0.0137**
	0.49	*2.46*	*3.46*	*4.68*	*5.25*	*4.37*	*4.91*		*-4.65*	*-2.48*	*-2.67*	*0.37*	*3.28*	*4.96*	*5.01*
3	0.0058	0.0074	0.0081	0.0125	0.0162	**0.0103**	**0.0126**	3	-0.0041	-0.0030	-0.0013	0.0015	0.0058	**0.0100**	**0.0101**
	1.55	*2.62*	*3.42*	*5.30*	*5.64*	*3.13*	*3.76*		*-2.67*	*-2.88*	*-1.60*	*1.78*	*4.19*	*4.22*	*3.67*
4	0.0050	0.0091	0.0090	0.0110	0.0142	**0.0092**	**0.0118**	4	-0.0042	0.0002	-0.0006	0.0005	0.0034	**0.0076**	**0.0091**
	1.24	*3.33*	*3.88*	*4.79*	*5.08*	*2.59*	*3.27*		*-2.51*	*0.21*	*-0.75*	*0.64*	*2.60*	*3.16*	*3.00*
RSQ5	0.0065	0.0074	0.0079	0.0095	0.0129	**0.0065**	**0.0091**	RSQ5	-0.0009	-0.0006	-0.0010	0.0003	0.0033	**0.0042**	**0.0071**
	1.78	*2.85*	*3.37*	*4.09*	*4.69*	*1.89*	*2.61*		*-0.60*	*-0.65*	*-1.38*	*0.43*	*2.57*	*1.83*	*2.64*

Table 4. R^2 and Price Momentum, alternative specifications

Average monthly raw and characteristic-adjusted returns on portfolios sorted by various R^2 and price momentum measures are reported over the period from July, 1964 to December, 2002. At the beginning of each month, stocks are ranked by a R^2 measure using NYSE breakpoints and placed into quintiles. Within each R^2 quintile, stocks are then sorted into quintiles based on past twelve month return or past six month return (skipping the most recent month). The value-weighted raw and adjusted returns on these double-sorted portfolios are computed over the following month and their average values and t-statistics (in *italics*) as well as the differences in returns between momentum quintile 5 and 1 within each R^2 quintile are reported. The adjusted returns employ a characteristic-based matching procedure which accounts for return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Panel A reports results for portfolios sorted by the full-sample *adjusted* R^2 (*adj.* R^2_{FS}) and cumulative raw return over the past year (Ret (-12:-2)). Panel B reports results for portfolios *independently* sorted by R^2_{FS} and cumulative raw return over the past year (Ret (-12:-2)). Panel C reports the equal-weighted portfolio returns sorted by R^2_{FS} and cumulative raw return over the past year (Ret (-12:-2)), where stocks with market capitalization less than the 10th percentile breakpoint for NYSE firms and price less than $5 are excluded to minimize market microstructure noises in the equal weighted portfolio returns. Panels D reports the returns for portfolios sorted by R^2_{FS} and cumulative raw return over the past six months, skipping the most recent month (Ret (-6:-2)).

Panel A: Double-Sorted Quintile Portfolios of adj. R^2_{FS} and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0083	0.0010	0.0055	0.0080	0.0111	**0.0194**	RSQ1	-0.0166	-0.0089	-0.0056	-0.0036	-0.0005	**0.0161**
	-2.14	*0.35*	*2.40*	*3.38*	*3.78*	*6.31*		*-9.37*	*-7.83*	*-5.49*	*-3.61*	*-0.37*	*6.15*
2	0.0019	0.0050	0.0095	0.0110	0.0148	**0.0129**	2	-0.0079	-0.0048	-0.0015	0.0001	0.0035	**0.0114**
	0.47	*1.80*	*3.99*	*4.58*	*4.91*	*3.82*		*-3.58*	*-5.01*	*-1.83*	*0.11*	*2.62*	*3.94*
3	0.0059	0.0074	0.0091	0.0124	0.0141	**0.0082**	3	-0.0033	-0.0022	-0.0011	0.0014	0.0035	**0.0068**
	1.52	*2.76*	*3.91*	*5.35*	*4.76*	*2.46*		*-1.71*	*-2.36*	*-1.40*	*1.40*	*2.46*	*2.41*
4	0.0080	0.0080	0.0077	0.0113	0.0159	**0.0078**	4	-0.0012	-0.0005	-0.0018	0.0012	0.0050	**0.0062**
	2.27	*3.13*	*3.43*	*5.12*	*5.77*	*2.49*		*-0.68*	*-0.53*	*-2.35*	*1.45*	*3.84*	*2.39*
RSQ5	0.0089	0.0088	0.0078	0.0110	0.0139	**0.0050**	RSQ5	0.0004	0.0001	-0.0006	0.0013	0.0041	**0.0037**
	2.53	*3.52*	*3.57*	*4.92*	*4.89*	*1.42*		*0.18*	*0.10*	*-0.99*	*1.70*	*2.85*	*1.32*

Panel B: Double-Sorted Quintile Portfolios of R^2_{FS} and Ret(-12:-2), Independent Sort

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0035	0.0052	0.0069	0.0085	0.0110	**0.0146**	RSQ1	-0.0126	-0.0051	-0.0042	-0.0034	-0.0004	**0.0122**
	-1.04	*2.17*	*3.17*	*3.61*	*3.93*	*5.56*		*-9.05*	*-4.42*	*-3.78*	*-2.97*	*-0.35*	*5.44*
2	0.0024	0.0060	0.0100	0.0101	0.0147	**0.0123**	2	-0.0074	-0.0042	-0.0009	-0.0008	0.0036	**0.0110**
	0.69	*2.36*	*4.32*	*4.44*	*5.23*	*4.96*		*-4.99*	*-4.66*	*-1.05*	*-0.96*	*2.97*	*5.10*
3	0.0051	0.0073	0.0102	0.0101	0.0144	**0.0093**	3	-0.0038	-0.0025	0.0000	-0.0009	0.0036	**0.0074**
	1.48	*2.90*	*4.36*	*4.53*	*5.22*	*3.49*		*-2.62*	*-2.51*	*0.01*	*-0.93*	*3.05*	*3.31*
4	0.0070	0.0086	0.0079	0.0105	0.0146	**0.0076**	4	-0.0021	-0.0004	-0.0016	0.0005	0.0040	**0.0061**
	2.07	*3.48*	*3.56*	*4.86*	*5.57*	*2.65*		*-1.30*	*-0.49*	*-1.94*	*0.61*	*3.56*	*2.62*
RSQ5	0.0086	0.0094	0.0081	0.0109	0.0139	**0.0053**	RSQ5	0.0003	0.0005	-0.0005	0.0012	0.0040	**0.0037**
	2.58	*3.85*	*3.68*	*4.98*	*5.19*	*1.76*		*0.15*	*0.49*	*-0.75*	*1.54*	*3.17*	*1.52*

Panel C: Double-Sorted Quintile Portfolios of R^2_{FS} and Ret(-12:-2), Equal-Weighted

	Equal-Weighted Raw Returns							Equal-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0031	0.0060	0.0097	0.0098	0.0118	**0.0150**	RSQ1	-0.0126	-0.0049	-0.0021	-0.0021	0.0006	**0.0132**
	-0.87	*2.42*	*4.26*	*4.26*	*4.21*	*6.09*		*-10.48*	*-5.64*	*-2.20*	*-2.14*	*0.54*	*6.35*
2	0.0069	0.0109	0.0124	0.0144	0.0180	**0.0110**	2	-0.0037	-0.0004	0.0007	0.0025	0.0063	**0.0100**
	1.87	*4.02*	*5.06*	*5.72*	*5.78*	*4.16*		*-2.92*	*-0.54*	*0.93*	*3.39*	*5.26*	*4.58*
3	0.0102	0.0113	0.0120	0.0151	0.0191	**0.0088**	3	-0.0001	0.0000	0.0005	0.0029	0.0070	**0.0070**
	2.70	*4.04*	*4.71*	*5.88*	*6.01*	*3.17*		*-0.05*	*-0.05*	*0.83*	*4.29*	*5.53*	*3.13*
4	0.0117	0.0102	0.0103	0.0127	0.0198	**0.0082**	4	0.0024	0.0003	0.0001	0.0022	0.0083	**0.0059**
	3.04	*3.89*	*4.49*	*5.46*	*6.35*	*2.22*		*1.20*	*0.38*	*0.20*	*2.98*	*5.35*	*2.00*
RSQ5	0.0124	0.0126	0.0113	0.0148	0.0195	**0.0071**	RSQ5	0.0025	0.0015	0.0003	0.0035	0.0077	**0.0053**
	3.18	*4.62*	*4.61*	*6.04*	*6.23*	*2.27*		*1.35*	*2.07*	*0.48*	*5.22*	*5.95*	*2.05*

Panel D: Double-Sorted Quintile Portfolios of R^2_{FS} and Ret(-6:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0040	0.0057	0.0065	0.0063	0.0095	**0.0135**	RSQ1	-0.0130	-0.0050	-0.0048	-0.0047	-0.0020	**0.0110**
	-1.03	*2.02*	*2.75*	*2.70*	*3.38*	*4.50*		*-7.51*	*-4.43*	*-4.74*	*-4.33*	*-1.57*	*4.27*
2	0.0035	0.0099	0.0103	0.0103	0.0120	**0.0085**	2	-0.0060	-0.0008	-0.0006	-0.0005	0.0006	**0.0066**
	0.89	*3.64*	*4.25*	*4.33*	*4.07*	*2.64*		*-2.89*	*-0.93*	*-0.67*	*-0.57*	*0.46*	*2.45*
3	0.0082	0.0078	0.0113	0.0111	0.0129	**0.0048**	3	-0.0013	-0.0021	0.0003	0.0005	0.0025	**0.0038**
	2.19	*2.88*	*4.88*	*4.78*	*4.33*	*1.49*		*-0.75*	*-2.29*	*0.33*	*0.58*	*1.69*	*1.43*
4	0.0087	0.0120	0.0091	0.0105	0.0125	**0.0038**	4	-0.0002	0.0023	-0.0007	0.0008	0.0021	**0.0024**
	2.55	*4.50*	*4.11*	*4.70*	*4.76*	*1.28*		*-0.15*	*2.13*	*-0.95*	*0.93*	*1.72*	*0.99*
RSQ5	0.0112	0.0101	0.0102	0.0089	0.0107	**-0.0004**	RSQ5	0.0024	0.0017	0.0011	-0.0002	0.0015	**-0.0009**
	3.25	*4.13*	*4.68*	*3.98*	*4.00*	*-0.14*		*1.38*	*2.14*	*1.68*	*-0.30*	*1.18*	*-0.34*

Table 5. Long-Run Performance of R^2-Sorted portfolios

Average monthly raw and characteristic-adjusted returns on portfolios sorted by the full-sample R^2 (R^2_{FS}) and cumulative raw return over various sorting periods are reported over the period from July, 1964 to December, 2002 for various holding periods. At the beginning of each month, stocks are ranked by R^2_{FS} using NYSE breakpoints and placed into quintiles. Within each R^2 quintile, stocks are then sorted into quintiles based on the return of the specified sorting periods. The value-weighted raw and adjusted returns on these double-sorted portfolios are computed every month over the specified holding periods. Average monthly returns and t-statistics (in *italics*) as well as the differences in returns between momentum quintile 5 and 1 within each R^2 quintile are reported for the different holding periods. The adjusted returns employs a characteristic-based matching procedure which accounts for return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997).

Panel A: Sorting Period=t-12:t-2, Holding Period =t (Same as Table 2 Panel A)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0067	0.0008	0.0056	0.0080	0.0114	**0.0181**	RSQ1	-0.0159	-0.0094	-0.0059	-0.0041	-0.0006	**0.0152**
	-1.83	*0.30*	*2.40*	*3.25*	*3.74*	*6.65*		*-10.65*	*-8.30*	*-6.15*	*-4.57*	*-0.55*	*6.70*
2	0.0023	0.0067	0.0101	0.0122	0.0156	**0.0133**	2	-0.0082	-0.0039	-0.0014	0.0003	0.0037	**0.0119**
	0.68	*2.44*	*4.20*	*4.92*	*5.01*	*5.14*		*-5.69*	*-4.34*	*-1.82*	*0.33*	*2.83*	*5.32*
3	0.0059	0.0091	0.0097	0.0130	0.0152	**0.0093**	3	-0.0040	-0.0018	-0.0015	0.0011	0.0036	**0.0076**
	1.82	*3.59*	*3.96*	*5.45*	*4.89*	*3.40*		*-2.91*	*-1.92*	*-2.05*	*1.26*	*2.49*	*3.32*
4	0.0090	0.0085	0.0088	0.0123	0.0165	**0.0075**	4	-0.0014	-0.0012	-0.0020	0.0012	0.0047	**0.0062**
	2.88	*3.46*	*3.87*	*5.41*	*5.69*	*2.66*		*-1.02*	*-1.38*	*-2.60*	*1.52*	*3.62*	*2.78*
RSQ5	0.0103	0.0105	0.0090	0.0122	0.0154	**0.0051**	RSQ5	0.0004	0.0006	-0.0008	0.0015	0.0046	**0.0042**
	3.65	*4.73*	*4.17*	*5.37*	*5.23*	*1.72*		*0.27*	*0.77*	*-1.24*	*2.11*	*3.14*	*1.81*

Panel B: Sorting Period=t-12:t-2, Holding Period=t:t+5

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0041	0.0012	0.0064	0.0082	0.0081	**0.0122**	RSQ1	-0.0133	-0.0090	-0.0048	-0.0035	-0.0028	**0.0105**
	-1.14	0.42	2.80	3.57	2.80	4.68		-8.97	-9.68	-5.82	-3.90	-2.50	4.85
2	0.0040	0.0080	0.0098	0.0115	0.0139	**0.0099**	2	-0.0067	-0.0032	-0.0019	-0.0001	0.0027	**0.0094**
	1.22	*3.07*	*4.20*	*4.79*	*4.47*	*4.38*		*-5.29*	*-4.57*	*-3.04*	*-0.09*	*2.29*	*4.94*
3	0.0072	0.0094	0.0108	0.0118	0.0144	**0.0072**	3	-0.0031	-0.0018	-0.0006	0.0004	0.0030	**0.0062**
	2.36	*3.76*	*4.59*	*5.05*	*4.79*	*3.13*		*-2.87*	*-2.51*	*-0.97*	*0.55*	*2.49*	*3.28*
4	0.0088	0.0088	0.0100	0.0111	0.0157	**0.0068**	4	-0.0013	-0.0016	-0.0008	0.0005	0.0041	**0.0054**
	3.10	*3.67*	*4.55*	*4.97*	*5.56*	*2.86*		*-1.19*	*-2.21*	*-1.33*	*0.92*	*3.68*	*3.04*
RSQ5	0.0091	0.0085	0.0087	0.0104	0.0132	**0.0041**	RSQ5	0.0001	-0.0002	0.0001	0.0012	0.0038	**0.0037**
	2.76	3.70	4.17	4.76	4.66	1.32		0.08	-0.27	0.11	2.23	3.05	1.46

Panel C: Sorting Period=t-12:t-2, Holding Period=t:t+11

Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0009	0.0032	0.0070	0.0080	0.0057	**0.0066**	RSQ1	-0.0109	-0.0075	-0.0045	-0.0035	-0.0046	**0.0064**
	-0.25	*1.14*	*3.05*	*3.44*	*1.93*	*2.80*		*-8.02*	*-9.05*	*-5.65*	*-4.13*	*-4.44*	*3.35*
2	0.0069	0.0095	0.0103	0.0107	0.0112	**0.0043**	2	-0.0044	-0.0020	-0.0014	-0.0008	0.0004	**0.0048**
	2.15	*3.75*	*4.46*	*4.43*	*3.68*	*2.25*		*-4.06*	*-3.16*	*-2.59*	*-1.38*	*0.38*	*3.08*
3	0.0094	0.0100	0.0110	0.0117	0.0123	**0.0029**	3	-0.0016	-0.0014	-0.0004	0.0005	0.0014	**0.0030**
	3.22	*4.12*	*4.77*	*5.06*	*4.20*	*1.49*		*-1.68*	*-2.33*	*-0.74*	*0.76*	*1.45*	*2.03*
4	0.0100	0.0100	0.0099	0.0104	0.0143	**0.0042**	4	-0.0002	-0.0009	-0.0008	0.0001	0.0030	**0.0033**
	3.71	*4.31*	*4.65*	*4.71*	*5.18*	*2.10*		*-0.25*	*-1.47*	*-1.52*	*0.26*	*3.16*	*2.27*
RSQ5	0.0097	0.0093	0.0091	0.0097	0.0120	**0.0024**	RSQ5	0.0006	0.0004	0.0003	0.0008	0.0028	**0.0022**
	3.17	*4.05*	*4.33*	*4.36*	*4.18*	*0.88*		*0.39*	*0.51*	*0.75*	*2.02*	*2.53*	*1.03*

Panel D: Sorting Period=t-12:t-2, Holding Period=t+12:t+35

Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	0.0063	0.0071	0.0083	0.0068	0.0015	**-0.0048**	RSQ1	-0.0044	-0.0044	-0.0039	-0.0043	-0.0076	**-0.0032**
	1.86	*2.66*	*3.54*	*2.82*	*0.50*	*-3.24*		*-5.27*	*-7.34*	*-5.89*	*-6.08*	*-9.35*	*-2.92*
2	0.0105	0.0108	0.0109	0.0094	0.0057	**-0.0049**	2	0.0003	-0.0007	-0.0006	-0.0012	-0.0033	**-0.0036**
	3.34	*4.36*	*4.62*	*3.79*	*1.86*	*-3.13*		*0.34*	*-1.37*	*-1.16*	*-2.17*	*-4.63*	*-3.35*
3	0.0119	0.0108	0.0101	0.0092	0.0077	**-0.0042**	3	0.0010	0.0000	-0.0001	-0.0009	-0.0012	**-0.0022**
	4.12	*4.41*	*4.29*	*3.74*	*2.61*	*-3.12*		*1.43*	*0.08*	*-0.17*	*-1.44*	*-1.69*	*-2.22*
4	0.0123	0.0104	0.0093	0.0095	0.0097	**-0.0026**	4	0.0020	0.0003	-0.0005	0.0000	0.0005	**-0.0016**
	4.58	*4.75*	*4.36*	*4.11*	*3.32*	*-1.81*		*2.50*	*0.57*	*-0.82*	*-0.04*	*0.53*	*-1.51*
RSQ5	0.0142	0.0114	0.0111	0.0108	0.0107	**-0.0035**	RSQ5	0.0033	0.0011	0.0008	0.0007	0.0006	**-0.0027**
	6.00	*5.45*	*5.35*	*4.99*	*4.26*	*-2.65*		*4.73*	*2.91*	*2.62*	*2.21*	*1.02*	*-2.90*

Panel E: Sorting Period=t-12:t-2, Holding Period=t+36:t+59

Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	0.0064	0.0082	0.0086	0.0073	0.0037	**-0.0028**	RSQ1	-0.0048	-0.0035	-0.0034	-0.0042	-0.0065	**-0.0017**
	2.02	*3.11*	*3.51*	*2.97*	*1.25*	*-2.19*		*-5.52*	*-5.33*	*-4.93*	*-5.51*	*-8.32*	*-1.62*
2	0.0105	0.0114	0.0115	0.0099	0.0078	**-0.0026**	2	-0.0012	-0.0006	-0.0001	-0.0012	-0.0030	**-0.0018**
	3.45	*4.64*	*4.77*	*3.96*	*2.66*	*-2.23*		*-1.53*	*-1.01*	*-0.21*	*-1.91*	*-3.94*	*-1.91*
3	0.0120	0.0116	0.0112	0.0104	0.0096	**-0.0023**	3	0.0005	0.0001	-0.0005	-0.0006	-0.0009	**-0.0014**
	4.26	*4.71*	*4.70*	*4.21*	*3.30*	*-2.08*		*0.66*	*0.17*	*-0.82*	*-0.92*	*-1.21*	*-1.50*
4	0.0117	0.0110	0.0107	0.0107	0.0101	**-0.0015**	4	0.0002	-0.0004	-0.0006	-0.0002	-0.0001	**-0.0003**
	4.64	*4.87*	*4.76*	*4.67*	*3.62*	*-1.26*		*0.35*	*-0.72*	*-1.09*	*-0.40*	*-0.09*	*-0.33*
RSQ5	0.0119	0.0110	0.0113	0.0113	0.0123	**0.0004**	RSQ5	0.0009	0.0006	0.0010	0.0009	0.0016	**0.0007**
	4.93	*5.06*	*5.19*	*5.02*	*4.80*	*0.40*		*1.53*	*1.67*	*3.08*	*2.20*	*2.65*	*0.82*

Panel F: Sorting Period=t-60:t-13, Holding Period=t

Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	0.0115	0.0088	0.0076	0.0071	0.0017	**-0.0097**	RSQ1	-0.0002	-0.0030	-0.0041	-0.0035	-0.0065	**-0.0063**
	2.91	*2.85*	*2.87*	*2.82*	*0.54*	*-3.54*		*-0.14*	*-3.03*	*-3.69*	*-2.88*	*-4.69*	*-3.13*
2	0.0137	0.0113	0.0114	0.0105	0.0042	**-0.0095**	2	0.0018	-0.0002	-0.0001	0.0004	-0.0049	**-0.0067**
	3.90	*4.28*	*4.56*	*4.09*	*1.34*	*-3.79*		*1.30*	*-0.27*	*-0.09*	*0.45*	*-3.85*	*-3.38*
3	0.0119	0.0132	0.0109	0.0089	0.0070	**-0.0050**	3	0.0003	0.0017	0.0001	-0.0012	-0.0012	**-0.0015**
	3.65	*5.30*	*4.36*	*3.39*	*2.24*	*-2.15*		*0.26*	*1.85*	*0.14*	*-1.08*	*-1.14*	*-0.88*
4	0.0131	0.0113	0.0107	0.0101	0.0083	**-0.0049**	4	0.0026	0.0006	0.0002	0.0002	-0.0002	**-0.0028**
	4.36	*4.79*	*4.58*	*4.26*	*2.76*	*-2.23*		*2.16*	*0.68*	*0.20*	*0.19*	*-0.20*	*-1.77*
RSQ5	0.0140	0.0107	0.0113	0.0098	0.0085	**-0.0055**	RSQ5	0.0034	0.0010	0.0017	0.0005	0.0002	**-0.0032**
	5.26	*4.73*	*4.95*	*4.23*	*2.82*	*-2.35*		*2.82*	*1.26*	*2.46*	*0.69*	*0.21*	*-1.92*

Table 6. Fama and MacBeth (1973) Cross-Sectional Regressions

This table presents results from Fama and MacBeth (1973) monthly cross-sectional regressions estimated monthly from July 1968 to December 2002 on the stocks that have a market capitalization greater than the 10th percentile breakpoint for NYSE firms and a price greater than $5. Every month, individual stock returns are regressed on log of size (market capitalization), log of book-to-market equity (BE/ME), previous month's return (Ret(-1:-1)), return over the previous year skipping the most recent month (Ret (-12:-2)), return over the previous five years skipping the most recent year (Ret (-60:-13)), R^2_{FS} after a logit transformation ($\ln(R^2_{FS}/(1-R^2_{FS}))$, a stock's cross-sectional R^2_{FS} ranking (R^2_{FS} rank), and interaction terms between logit R^2_{FS} or R^2_{FS} rank with Ret(-12:-2) or Ret(-60:-13). The time-series averages of the cross-sectional regression coefficients and their time-series t-statistics (in *italic*) are reported.

Regression	ln(Size)	ln(BE/ME)	Ret(-1:-1)	Ret(-12:-2)	Ret(-60:-13)	*logit* R^2_{FS}	*logit* R^2_{FS}× Ret(-12:-2)	*logit* R^2_{FS}× Ret(-60:-13)	R^2_{FS} rank	R^2_{FS} *rank*× Ret(-12:-2)	R^2_{FS} *rank*× Ret(-60:-13)
(1)	-0.0002	0.0024	-0.0486	0.0093	-0.0010						
	-0.42	*3.17*	*-9.77*	*4.22*	*-2.68*						
(2)	-0.0025	0.0017	-0.0497	0.0094	-0.0007	0.0060					
	-4.90	*2.13*	*-10.09*	*4.36*	*-1.90*	*9.44*					
(3)	-0.0024	0.0017	-0.0500	0.0051	-0.0007	0.0059	-0.0025				
	-4.79	*2.12*	*-10.21*	*1.55*	*-1.90*	*9.32*	*-2.34*				
(4)	-0.0025	0.0018	-0.0499	0.0093	0.0007	0.0051		0.0008			
	-4.86	*2.19*	*-10.13*	*4.33*	*1.24*	*8.08*		*3.35*			
(5)	-0.0024	0.0017	-0.0502	0.0049	0.0007	0.0052	-0.0026	0.0007			
	-4.77	*2.16*	*-10.24*	*1.52*	*1.14*	*8.09*	*-2.42*	*3.18*			
(6)	-0.0023	0.0018	-0.0494	0.0095	-0.0008				0.0030		
	-4.56	*2.21*	*-10.04*	*4.37*	*-2.12*				*8.05*		
(7)	-0.0022	0.0018	-0.0497	0.0128	-0.0008				0.0030	-0.0013	
	-4.55	*2.20*	*-10.15*	*5.75*	*-2.10*				*8.25*	*-2.14*	
(8)	-0.0022	0.0018	-0.0496	0.0093	-0.0017				0.0025		0.0004
	-4.54	*2.27*	*-10.10*	*4.33*	*-4.02*				*6.90*		*3.15*
(9)	-0.0022	0.0018	-0.0499	0.0128	-0.0016				0.0025	-0.0014	0.0004
	-4.55	*2.25*	*-10.21*	*5.76*	*-3.94*				*7.15*	*-2.25*	*3.19*

Table 7. Residual R^2 and Price Momentum

Average monthly raw and characteristic-adjusted returns of portfolios sorted by various residual R^2 measures and price momentum are reported. At the beginning of each month, stocks are ranked by a residual R^2 measure using NYSE breakpoints and placed into quintiles. Within each residual R^2 quintile, stocks are then sorted into quintiles based on past twelve month return (skipping the most recent month). The value-weighted raw and adjusted returns on these double-sorted portfolios are computed over the following month and their average values and t-statistics (in *italics*) as well as the differences in returns between momentum quintile 5 and 1 within each residual R^2 quintile are reported. The adjusted returns employs a characteristic-based matching procedure which accounts for return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). The residual R^2 are estimated using annual cross-sectional regressions where the full-sample R^2 is regressed on size (Panel A); size, analyst coverage and institutional ownership (Panel B); size, analyst coverage, institutional ownership, and fundamental R^2 (Panel C); size, analyst coverage, institutional ownership, fundamental R^2, and return volatility (Panel D); size, analyst coverage, institutional ownership, fundamental R^2, return volatility, and dispersion of analyst forecasts (Panel E); size and share turnover (Panel F); size and market illiquidity (Panel G). The residual from the regressions are used to form double-sorted portfolios with return over the past year (Ret(-12:-2)). The results cover the period July, 1964 to December, 2002 for Panels A, F, and G, and July, 1981 to December, 2002 for Panels B to E.

Panel A: Double-Sorted Quintile Portfolios of Res. R^2 (Size) and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0074	0.0011	0.0056	0.0093	0.0119	**0.0192**	RSQ1	-0.0141	-0.0065	-0.0039	-0.0015	-0.0003	**0.0138**
	-1.91	*0.39*	*2.35*	*4.17*	*4.21*	*5.57*		*-7.28*	*-4.99*	*-3.59*	*-1.57*	*-0.24*	*5.36*
2	0.0004	0.0053	0.0078	0.0120	0.0143	**0.0139**	2	-0.0075	-0.0039	-0.0013	0.0009	0.0038	**0.0113**
	0.10	*1.90*	*3.24*	*5.09*	*4.89*	*4.35*		*-4.19*	*-3.03*	*-1.35*	*0.85*	*2.61*	*4.20*
3	0.0051	0.0076	0.0094	0.0113	0.0148	**0.0096**	3	-0.0036	-0.0008	0.0002	0.0010	0.0039	**0.0075**
	1.33	*2.82*	*4.07*	*4.80*	*4.96*	*2.74*		*-1.86*	*-0.88*	*0.25*	*1.02*	*2.58*	*2.59*
4	0.0074	0.0101	0.0088	0.0119	0.0156	**0.0082**	4	-0.0016	0.0002	-0.0003	0.0018	0.0051	**0.0067**
	1.99	*3.85*	*3.68*	*5.15*	*5.39*	*2.47*		*-0.85*	*0.22*	*-0.37*	*2.24*	*3.48*	*2.37*
RSQ5	0.0099	0.0092	0.0095	0.0116	0.0155	**0.0055**	RSQ5	0.0014	0.0001	0.0004	0.0019	0.0054	**0.0040**
	2.63	*3.37*	*4.12*	*5.05*	*5.22*	*1.52*		*0.66*	*0.09*	*0.55*	*2.42*	*3.48*	*1.35*

Panel B: Double-Sorted Quintile Portfolios of Res. R^2 (Size, Analyst, Inst) and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0029	0.0048	0.0121	0.0132	0.0164	**0.0193**	RSQ1	-0.0127	-0.0083	-0.0018	-0.0017	0.0019	**0.0146**
	-0.57	*1.16*	*3.97*	*4.62*	*4.73*	*4.29*		*-4.43*	*-4.24*	*-1.38*	*-1.85*	*1.29*	*4.16*
2	0.0033	0.0103	0.0122	0.0134	0.0170	**0.0138**	2	-0.0080	-0.0032	-0.0016	-0.0007	0.0037	**0.0117**
	0.70	*2.76*	*3.77*	*4.19*	*4.55*	*3.25*		*-3.08*	*-1.99*	*-1.48*	*-0.73*	*1.97*	*3.20*
3	0.0042	0.0119	0.0116	0.0125	0.0151	**0.0109**	3	-0.0064	-0.0013	-0.0016	-0.0007	0.0023	**0.0086**
	0.92	*3.55*	*3.49*	*3.99*	*4.00*	*2.92*		*-2.75*	*-0.86*	*-1.34*	*-0.68*	*1.55*	*2.86*
4	0.0097	0.0149	0.0122	0.0126	0.0169	**0.0072**	4	-0.0020	0.0006	-0.0012	-0.0005	0.0043	**0.0064**
	2.11	*4.66*	*3.90*	*3.96*	*4.08*	*1.79*		*-0.87*	*0.44*	*-1.09*	*-0.42*	*2.23*	*1.87*
RSQ5	0.0149	0.0127	0.0155	0.0171	0.0211	**0.0062**	RSQ5	0.0025	-0.0008	0.0014	0.0033	0.0080	**0.0055**
	3.29	*3.49*	*4.56*	*5.05*	*4.45*	*1.33*		*1.10*	*-0.50*	*1.05*	*2.21*	*3.25*	*1.42*

Panel C: Double-Sorted Quintile Portfolios of Res. R^2 (Size, Analyst, Inst, FRSQ) and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	0.0007	0.0077	0.0118	0.0135	0.0168	**0.0161**	RSQ1	-0.0098	-0.0058	-0.0027	-0.0012	0.0021	**0.0120**
	0.15	*1.93*	*4.06*	*4.80*	*4.71*	*3.60*		*-3.43*	*-2.95*	*-2.13*	*-1.29*	*1.32*	*3.37*
2	0.0037	0.0119	0.0119	0.0131	0.0181	**0.0144**	2	-0.0082	-0.0019	-0.0018	-0.0008	0.0044	**0.0126**
	0.80	*3.27*	*3.79*	*4.20*	*4.78*	*3.41*		*-3.25*	*-1.17*	*-1.65*	*-0.68*	*2.27*	*3.50*
3	0.0067	0.0118	0.0126	0.0120	0.0144	**0.0077**	3	-0.0047	-0.0013	-0.0006	-0.0012	0.0022	**0.0069**
	1.55	*3.61*	*3.82*	*3.83*	*3.64*	*2.07*		*-2.04*	*-0.85*	*-0.47*	*-1.05*	*1.29*	*2.19*
4	0.0106	0.0152	0.0131	0.0125	0.0171	**0.0066**	4	-0.0013	0.0011	-0.0001	-0.0010	0.0047	**0.0060**
	2.36	*4.72*	*4.11*	*3.84*	*4.11*	*1.61*		*-0.57*	*0.79*	*-0.09*	*-0.76*	*2.21*	*1.75*
RSQ5	0.0160	0.0119	0.0158	0.0163	0.0214	**0.0054**	RSQ5	0.0029	-0.0012	0.0022	0.0023	0.0080	**0.0051**
	3.45	*3.27*	*4.71*	*4.72*	*4.43*	*1.07*		*1.14*	*-0.74*	*1.74*	*1.57*	*3.05*	*1.21*

Panel D: Double-Sorted Quintile Portfolios of Res. R^2 (Size, Analyst, Inst, FRSQ, TVOL) and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0012	0.0103	0.0110	0.0152	0.0160	**0.0172**	RSQ1	-0.0127	-0.0035	-0.0036	0.0001	0.0020	**0.0147**
	-0.24	*2.93*	*3.72*	*4.93*	*4.13*	*3.40*		*-3.91*	*-1.84*	*-2.37*	*0.05*	*0.92*	*3.42*
2	0.0052	0.0116	0.0125	0.0132	0.0183	**0.0131**	2	-0.0062	-0.0020	-0.0013	-0.0012	0.0036	**0.0098**
	1.19	*3.50*	*4.18*	*4.38*	*4.97*	*3.25*		*-2.66*	*-1.45*	*-1.13*	*-1.10*	*1.97*	*3.04*
3	0.0079	0.0116	0.0112	0.0142	0.0184	**0.0105**	3	-0.0046	-0.0017	-0.0022	0.0003	0.0049	**0.0095**
	1.74	*3.44*	*3.59*	*4.66*	*4.70*	*2.40*		*-1.70*	*-1.09*	*-2.05*	*0.28*	*2.30*	*2.42*
4	0.0045	0.0139	0.0131	0.0117	0.0148	**0.0103**	4	-0.0067	0.0000	-0.0001	-0.0012	0.0016	**0.0083**
	0.94	*4.00*	*4.24*	*3.59*	*3.84*	*2.58*		*-2.61*	*-0.02*	*-0.09*	*-1.10*	*0.95*	*2.53*
RSQ5	0.0140	0.0143	0.0099	0.0173	0.0188	**0.0048**	RSQ5	0.0030	0.0000	-0.0020	0.0030	0.0061	**0.0031**
	2.70	*3.72*	*2.80*	*5.03*	*4.29*	*1.07*		*1.13*	*-0.01*	*-1.43*	*2.41*	*2.93*	*0.84*

Panel E: Double-Sorted Quintile Portfolios of Res. R^2 (Size, Analyst, Inst, FRSQ, TVOL, DISP) and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	0.0047	0.0136	0.0121	0.0156	0.0161	**0.0115**	RSQ1	-0.0083	-0.0009	-0.0026	0.0004	0.0019	**0.0102**
	1.22	*4.55*	*4.17*	*5.41*	*4.51*	*3.14*		*-4.43*	*-0.59*	*-2.11*	*0.27*	*1.08*	*3.44*
2	0.0131	0.0085	0.0121	0.0124	0.0198	**0.0067**	2	-0.0013	-0.0042	-0.0016	-0.0023	0.0052	**0.0065**
	3.46	*2.54*	*3.86*	*4.28*	*5.63*	*1.80*		*-0.64*	*-2.82*	*-1.14*	*-1.74*	*3.10*	*2.11*
3	0.0114	0.0138	0.0123	0.0134	0.0154	**0.0039**	3	-0.0021	0.0004	-0.0008	-0.0003	0.0012	**0.0033**
	2.92	*4.32*	*3.92*	*4.38*	*4.41*	*1.25*		*-1.06*	*0.30*	*-0.66*	*-0.30*	*0.88*	*1.21*
4	0.0128	0.0133	0.0107	0.0127	0.0158	**0.0030**	4	-0.0007	0.0002	-0.0019	-0.0017	0.0021	**0.0028**
	3.05	*4.03*	*3.28*	*3.70*	*4.24*	*0.84*		*-0.34*	*0.19*	*-1.38*	*-1.23*	*1.23*	*0.92*
RSQ5	0.0169	0.0134	0.0123	0.0184	0.0190	**0.0021**	RSQ5	0.0032	0.0005	-0.0011	0.0043	0.0053	**0.0021**
	3.85	*3.51*	*3.47*	*5.30*	*4.60*	*0.60*		*1.45*	*0.29*	*-0.82*	*3.23*	*2.98*	*0.68*

Panel F: Double-Sorted Quintile Portfolios of Res. R^2_{FS} (Size, TURN) and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0087	0.0003	0.0065	0.0078	0.0116	**0.0202**	RSQ1	-0.0154	-0.0076	-0.0028	-0.0022	-0.0011	**0.0143**
	-2.16	*0.10*	*2.61*	*3.40*	*3.86*	*5.47*		*-7.29*	*-5.19*	*-2.26*	*-2.35*	*-0.80*	*5.06*
2	0.0019	0.0054	0.0069	0.0133	0.0124	**0.0105**	2	-0.0066	-0.0033	-0.0011	0.0018	0.0014	**0.0080**
	0.49	*1.91*	*2.74*	*5.34*	*4.57*	*3.12*		*-3.33*	*-2.50*	*-1.06*	*1.61*	*1.09*	*2.92*
3	0.0037	0.0074	0.0090	0.0105	0.0140	**0.0103**	3	-0.0043	-0.0015	0.0001	0.0005	0.0041	**0.0083**
	1.02	*2.72*	*3.84*	*4.44*	*4.67*	*3.18*		*-2.36*	*-1.43*	*0.12*	*0.47*	*2.55*	*3.01*
4	0.0073	0.0094	0.0095	0.0111	0.0154	**0.0082**	4	-0.0011	-0.0003	0.0004	0.0011	0.0052	**0.0063**
	1.94	*3.64*	*4.15*	*4.99*	*5.46*	*2.43*		*-0.56*	*-0.36*	*0.53*	*1.20*	*3.72*	*2.19*
RSQ5	0.0095	0.0098	0.0096	0.0111	0.0174	**0.0079**	RSQ5	0.0010	0.0005	0.0002	0.0016	0.0074	**0.0065**
	2.66	*3.97*	*4.38*	*5.00*	*5.88*	*2.26*		*0.54*	*0.54*	*0.23*	*2.01*	*4.87*	*2.34*

Panel G: Double-Sorted Quintile Portfolios of Res. R^2_{FS} (Size, ILLIQ) and Ret(-12:-2)

	Value-Weighted Raw Returns							Value-Weighted Characteristic-Adjusted Returns					
	Mom1	2	3	4	Mom5	5-1		Mom1	2	3	4	Mom5	5-1
RSQ1	-0.0068	0.0014	0.0056	0.0082	0.0118	**0.0187**	RSQ1	-0.0134	-0.0064	-0.0033	-0.0018	-0.0003	**0.0131**
	-1.73	*0.48*	*2.27*	*3.68*	*4.25*	*5.35*		*-6.47*	*-4.63*	*-2.86*	*-1.88*	*-0.26*	*4.88*
2	0.0008	0.0055	0.0063	0.0128	0.0137	**0.0129**	2	-0.0078	-0.0036	-0.0025	0.0017	0.0029	**0.0107**
	0.21	*1.98*	*2.56*	*5.49*	*4.67*	*3.97*		*-4.03*	*-2.74*	*-2.60*	*1.61*	*2.08*	*3.94*
3	0.0047	0.0073	0.0099	0.0121	0.0150	**0.0103**	3	-0.0041	-0.0015	0.0003	0.0014	0.0041	**0.0082**
	1.20	*2.72*	*4.27*	*5.15*	*5.03*	*2.81*		*-2.07*	*-1.54*	*0.27*	*1.46*	*2.59*	*2.72*
4	0.0070	0.0095	0.0090	0.0118	0.0158	**0.0088**	4	-0.0016	0.0000	0.0003	0.0020	0.0054	**0.0071**
	1.89	*3.62*	*3.78*	*5.04*	*5.45*	*2.66*		*-0.86*	*-0.02*	*0.32*	*2.55*	*3.72*	*2.53*
RSQ5	0.0097	0.0092	0.0092	0.0113	0.0154	**0.0058**	RSQ5	0.0011	0.0001	0.0001	0.0018	0.0053	**0.0042**
	2.56	*3.35*	*4.01*	*4.89*	*5.17*	*1.57*		*0.53*	*0.09*	*0.14*	*2.10*	*3.37*	*1.38*

Figure 1. Cumulative Momentum Profits by R^2 Quintiles

The cumulative average monthly raw (Figure 1A) and characteristic-adjusted (Figure 1B) 5-1 momentum (Ret(-12:-2)) spreads over the holding period month t to month t+59 are plotted for each R^2_{FS} quintile. The adjusted returns employ a characteristic-based matching procedure which accounts for return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997).