Is R^2 a Measure of Market Inefficiency?*

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Abstract

This paper provides a critical evaluation of a widely made argument that stock prices in markets with lower return R^2 are more efficient. We show that in a standard rational expectations model, return R^2 is independent of the amount of information incorporated into stock prices. Furthermore, an alternative model in which stock price fluctuations are driven by investor sentiment leads to an opposite prediction that lower return R^2 is associated with stronger medium-term price momentum and long-term price reversal, two commonly believed signs of market inefficiency. By examining stock returns both in the U.S. and internationally, we find empirical evidence consistent with this contrasting prediction. Overall, our analysis casts doubt on the argument that low return R^2 is a measure of market efficiency.

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1 Introduction

A stock's return R^2 is the R^2 statistic derived from regressing the stock's returns either on a single market index or on multiple common factors. Roll (1988) initially finds that return R^2 of U.S. stocks is low, indicating high firm-specific return variations. Subsequently, Morck, Yeung, and Yu (2000), which we refer to as MYY hereafter, show that return R^2 is also low among other advanced stock markets, while high among emerging markets, even after controlling for stocks' fundamental R^2. They further document that differences in public investor property rights explain the cross-country differences in return R^2, a finding which they attribute to stronger public investor property rights promoting trading on firm-specific information. Based on these findings, they intuitively argue that higher return R^2 can be used as a measure of price inefficiency of stock markets (or equivalently, lower return R^2 as a measure of market efficiency). This R^2-based inefficiency measure has gained increasing popularity in recent years and is widely used in various empirical studies of corporate investment and emerging market development, e.g., Wurgler, (2000), Durnev, et al. (2003), Durnev, Morck, and Yeung (2004), Jin and Myers (2006), and Chen, Goldstein, and Jiang (2006).

However, this market-efficiency interpretation of lower return R^2 remains controversial. From the theoretical perspective, MYY do not offer any model to establish a clear link between return R^2 and market efficiency. Such a link necessarily builds on the premise that idiosyncratic stock return variance reflects information about stocks' economic fundamentals. Two issues potentially undermine this premise however. First, within standard rational expectations models, it is difficult to simply treat stock return variance as equivalent to information flow in light of the insight of West (1988), Ross (1989), and Campbell, et al. (2001) that information flow affects the timing of investors' uncertainty resolution process but does not affect the total amount of uncertainty resolution over time or the total amount of stock return variance. Second, as highlighted by the burgeoning behavioral finance literature, stock price fluctuations may reflect either fundamental information flow or investor sentiment (see literature reviews of Hirshleifer, 2001 and Barberis and Thaler, 2003). To the extent that investor sentiment may drive stock return variance (e.g., Shiller, 1981), lower return R^2

may actually capture market inefficiency rather than efficiency.

From the empirical perspective, the market-efficiency interpretation of lower return R^2 does not square with two strands of empirical findings. First, Chan and Hameed (2006) and Brandt, et al. (2010) show that stocks with lower return R^2 tend to be smaller, have lower institutional ownership, analyst coverage and liquidity. Second, several studies, e.g., Chan and Hameed (2006), Kelly (2007), Ashbaugh-Skaife, Gassen and LaFond (2006), Griffin, Kelly, and Nadari (2010), Teoh, Yang and Zhang (2007), Dasgupta, Gan and Gao (2010), Bartram, Brown and Stulz (2012) directly analyze the relationship between return R^2 and measures of stock price informativeness using both U.S. and international data and find no consistent evidence.

In this paper, we provide a critical assessment of return R^2 as a measure of market efficiency from both theoretical and empirical perspectives. First, we develop a simple model to examine how the reaction of a representative investor to firm-specific information affects the stock's return R^2 and price efficiency. We consider three distinct settings. In the rational benchmark setting, the investor rationally reacts to the information available. In this setting, the more firm-specific information the investor processes in a given period, the more the investor updates his belief regarding the stock's fundamental value. As a consequence, the stock has greater idiosyncratic return variance during the period. However, there is less remaining uncertainty and thus smaller idiosyncratic return variance in the future. Overall, the investor's rational reaction to information makes the stock return unpredictable, and, more important, the stock's return R^2 independent of the amount of firm-specific information available to the investor. This rational benchmark highlights that the theoretical underpinning of the link between return R^2 and market efficiency is far more elusive than often perceived.

To account for the possibility that stock return variance may reflect investor sentiment, we also examine two other settings in which the representative investor has biased reactions to firm-specific information available to him. We show that when the investor either over- or under-reacts to his firm-specific information, contrary to the rational benchmark, the stock's return R^2 is determined both by the amount of firm-specific information available and the investor's behavioral bias, and this inefficiency can be captured by serially correlated returns. Adopting the spirit of Daniel, Hirshleifer, and Subrahmanyam (1998) with continued investor overreactions to firm-specific information, our model shows that lower return R^2 is accompanied by more pronounced medium-term price momentum and long-term price reversal, two widely observed asset price anomalies (e.g., Jegadeesh and Titman (1993, 2001) and Lee and Swaminathan (2000)). In sharp contrast to the argument of MYY, the implication from the behavioral model directly links low return R^2 to market inefficiency rather than efficiency.

On the empirical side, we examine this model implication in the stock returns of the U.S. and a set of international countries including those originally analyzed by MYY. In analyzing the U.S. stock returns, we first sort stocks into different R^2 quintiles and then compare the profits from pursuing a momentum strategy within each of the R^2 quintiles. The momentum strategy involves buying winner stocks and shorting loser stocks based on their past 12-month returns and holding these positions over different holding periods. We find that the momentum strategy generates significantly higher profits (either raw or risk adjusted) over medium-term holding periods of one or six months in low R^2 quintiles than in high R^2 quintiles. This pattern confirms that lower R^2 is associated with stronger medium-term price momentum. Furthermore, over long-term holding periods from two years to three years and from four years to five years after portfolio formation, the momentum strategy leads to significantly negative profits in low R^2 quintiles although not in high R^2 quintiles. This difference indicates stronger long-term price reversal of low R^2 stocks. In analyzing the international stock returns, we separately measure average return R^2 of stocks in each of the countries in our sample and the profit from using the momentum strategy in each country by forming momentum portfolios based on past 6-month returns and holding the portfolios for one month. Across the countries, we find that low R^2 countries tend to have significantly stronger medium-term momentum profits than high R^2 countries. Overall, these findings support the implication of the behavioral model that investor sentiment contributes to stock price fluctuations and, as a result, lower return R^2 may reflect price inefficiency rather than efficiency.

The paper is organized as follows. Section 2 uses three different settings to analyze the link between return R^2 and stock market efficiency. In Section 3, we empirically examine the relationship of return R^2 with medium-term price momentum and long-term price reversal by employing stock return data from the U.S. and a set of international countries. Section 4 concludes the paper.

2 Theoretical Perspectives

From a theoretical point of view, the amount of information available to investors about a stock, together with how investors react to the information, jointly determine the stock's price dynamics. In this section, we provide a simple and canonical model to delineate the relationship between return R^2 and price efficiency along these two dimensions. We separately examine three distinct settings: 1) a rational benchmark in which investors efficiently process available information; 2) a biased-reaction case in which investors over- or under-react to available information; and 3) a time-varying overreaction case in which investors' overreactions to available information change over time.

2.1 Rational Benchmark

We first examine a rational benchmark, in which the representative investor rationally reacts to available information. There is a risky stock with three dates: $t = 0, 1, 2$. The stock generates a final payoff at $t = 2$, which is unobservable before $t = 2$. The final payoff is determined by a linear combination of two random components:

$$f = \beta u + v$$

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 Gaussian distribution.

The investor cannot observe the two fundamental factors u and v before date 2. Thus, his learning process determines the stock's price dynamics on dates 0 and 1. For simplicity, we assume that the representative investor is risk neutral and can borrow and lend at a risk-free interest rate normalized to 0.[1] Suppose that on date 0 the investor's prior beliefs

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

about the two fundamental 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 zero means. τ_u and τ_v are the respective precision of the investor's prior beliefs about the two fundamental factors. Thus, $1/\tau_u$ and $1/\tau_v$ represent the initial uncertainty faced by the investor.

On date 1, the investor observes two signals, s_u and s_v, about the two fundamental factors, respectively:

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

where ϵ_u and ϵ_u are random noise in the two signals, which are mutually independent and are independent of u and v. They also have a Gaussian distribution with zero means and variances of $1/\tau_{s,u}$ and $1/\tau_{s,v}$, respectively. The parameters $\tau_{s,u}$ and $\tau_{s,v}$ are the precision of the two signals and capture the amount of market and firm specific information available to the representative investor. Essentially, the amount of information incorporated by all investors in the market through their aggregate learning and trading are summarized into the two signals available to the representative investor in our model.

The two-period model serves to highlight the investor's uncertainty resolution process and the resulting asset price dynamics over time. During the first period from $t = 0$ to $t = 1$, the investor uses signals s_u and s_v to update his belief about asset fundamentals and to reduce the uncertainty he faces. The stock price fluctuates in response to the investor's learning process. During the second period from $t = 1$ to $t = 2$, the stock price movements are determined by the resolution of the remaining uncertainty when the stock's final payoff is realized.

Bayes rule implies that the investor's posterior beliefs at $t = 1$ about u and v are also Gaussian with the means given by

$$E(u|s_u) = \frac{\tau_{s,u}}{\tau_u + \tau_{s,u}} s_u, \text{ and } E(v|s_v) = \frac{\tau_{s,v}}{\tau_v + \tau_{s,v}} s_v.$$

The investor's risk neutrality implies that the stock price on each date is determined by the investor's expected payoff:

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

Note that in our model, shocks are normally distributed and additive, and as a result, prices (p) are also normally distributed. This setting is equivalent to one in which prices (P) are lognormally distributed and $p = \ln(P)$, price changes (Δp) are essentially returns ($\Delta \ln(P)$) and the volatility of price changes are return volatilities.

We focus on the effects of $\tau_{s,v}$, the precision of the firm-specific signal, which captures the amount of firm-specific information available to the investor. It should be clear that if the investor rationally processes the information available to him, the stock price fully reflects the information and its future price change is unpredictable. Furthermore, more precise information to the investor leads to more informative stock price p_1 on date 1.

The information available to the investor also affects the stock price dynamics. During the first period, the return variance is

$$
\begin{aligned}
Var\left(p_1 - p_0\right) &= Var\left[\beta \frac{\tau_{s,u}}{\tau_u + \tau_{s,u}} s_u\right] + Var\left[\frac{\tau_{s,v}}{\tau_v + \tau_{s,v}} s_v\right] \\
&= \beta^2 \frac{\tau_{s,u}}{\tau_u\left(\tau_u + \tau_{s,u}\right)} + \frac{\tau_{s,v}}{\tau_v\left(\tau_v + \tau_{s,v}\right)}
\end{aligned}
$$

where the two terms correspond to price fluctuations caused by the investor's belief updating about the market and firm-specific factors. It is straightforward to see that each term increases with the precision of the investor's information (i.e., $\tau_{s,u}$ and $\tau_{s,v}$).

In empirical analysis, return R^2 of a stock is commonly measured by regressing the stock's return onto the market return and other common factors. Such a measure corresponds to the fraction of return variance explained by the market factor in our model. During the first period from $t = 0$ to $t = 1$, the fraction of the return variance explained by the market factor is

$$
\frac{\beta^2 \frac{\tau_{s,u}}{\tau_u(\tau_u+\tau_{s,u})}}{\beta^2 \frac{\tau_{s,u}}{\tau_u(\tau_u+\tau_{s,u})} + \frac{\tau_{s,v}}{\tau_v(\tau_v+\tau_{s,v})}},
$$

which decreases with $\tau_{s,v}$, the precision of the investor's firm-specific information. In other words, if the investor receives more firm-specific information in the first period, the stock's return R^2 for this period decreases. This property is consistent with the argument of MYY that lower return R^2 is associated with stock prices incorporating more firm-specific information.

However, this one-period result can be misleading as the average return R^2 for the full model period paints a very different story. Across both periods of the model, the total return variance is

$$\Sigma \equiv Var(p_1 - p_0) + Var(p_2 - p_1) = \frac{\beta^2}{\tau_u} + \frac{1}{\tau_v},$$

where $\frac{\beta^2}{\tau_u}$ and $\frac{1}{\tau_v}$ correspond to market and firm-specific return variance components, respectively. Both components are *independent* of the amount of market and firm-specific information ($\tau_{s,u}$ and $\tau_{s,v}$), and they are only determined by the initial fundamental uncertainty. This is because stock price fluctuations across the full horizon reflect the investor's uncertainty resolution process. As mentioned earlier, more firm-specific information at $t = 1$ results in greater uncertainty resolution and greater firm-specific return variance. But it leaves less remaining uncertainty to be resolved during the second period and results in lower firm-specific return variance. As a result, the total firm-specific return variance (and the total amount of firm-specific uncertainty resolution) is independent of the investor's information at $t = 1$. See West (1988), Ross (1989), and Campbell, et al. (2001) for this insight regarding the irrelevance of information flow to long-run asset return variance.

Thus, the return R^2 across the full horizon, which corresponds to the fraction of the total return variance explained by the market factor, is also independent of the precision of the investor's information about either the market or firm-specific factor:

$$R^2 = \frac{\frac{\beta^2}{\tau_u}}{\frac{\beta^2}{\tau_u} + \frac{1}{\tau_v}},$$

This result is in sharp contrast to the argument of MYY: despite the fact that more firm-specific information leads to more informative stock prices, it has no effect on the stock's return R^2 over the full horizon.

We summarize our analysis in the rational benchmark setting in the following proposition:

Proposition 1. *If the representative investor rationally reacts to available information, more firm-specific information leads to more informative stock price but has no effect on the stock's return* R^2 *over the full horizon.*

The empirical implication of Proposition 1 is that return R^2 that is measured using multi-period observations over a long period of time should be independent of the amount of firm-level information with rational investors. This intuition can be extended to a stationary, multi-period, equilibrium. In such settings, there are shocks to asset fundamentals every period. In each period, the return variance is driven by uncertainty resolution due to investors' learning of new shocks, as well as the resolution of the remaining uncertainty of the previously partially learned shocks. In general, more information available increases the former but decreases the latter, leaving the rate of total uncertainty resolution unchanged. As a result, the fraction of firm-specific variance in the stock's total return variance remains constant for each period and is independent of the rate of information flow. Thus, if investors rationally respond to information, we should expect the average return R^2 to be independent of the amount of firm-level information.

2.2 Biased Investor Reactions

The rational benchmark analyzed in Section 2.1 shows that despite the appeal to use low return R^2 as a measure of market efficiency as several previous studies have done, the link between return R^2 and the amount of firm-specific information *cannot* be established in a rational framework. Perhaps such a link would arise if the investor has irrational reactions to information. The burgeoning empirical finance literature has documented ample evidence suggesting that investors may under- or over-react to information in different situations. See Hirshleifer (2001) and Barberis and Thaler (2003) for extensive reviews of the evidence. Motivated by these empirical findings, in this and the next subsection, we will examine two alternative settings, one in which the investor either over- or under-reacts to firm-specific information available to him, and the other in which the investor has continued overreactions.

This subsection presents the setting with either investor over- or under-reactions. Without loss of generality, we focus on biases in the investor's reaction to firm-specific information. Specifically, we extend the benchmark setting by assuming that the investor misestimates the precision of the signal s_v about the firm-specific factor by a multiple of $\phi > 0$, although he correctly perceives the precision of the signal s_u about the market factor. If $\phi = 1$, the investor correctly estimates to the precision of s_v. If $\phi > 1$, the investor over-estimates the precision, which, in turn, leads to an overreaction to the signal. If $\phi < 1$, the investor under-estimates the precision, which, in turn, leads to an underreaction. We call ϕ the investor's biased reaction parameter.

Bayes rule implies that at $t = 1$ the investor's posterior beliefs about the two fundamental factors are

$$E(u|s_u) = \frac{\tau_{s,u}}{\tau_u + \tau_{s,u}} s_u \text{ and } E(v|s_v) = \frac{\phi\tau_{s,v}}{\tau_v + \phi\tau_{s,v}} s_v.$$

Note that the investor's reaction coefficient to s_v, $\frac{\phi\tau_{s,v}}{\tau_v+\phi\tau_{s,v}}$, increases with the investor's biased reaction parameter ϕ. Based on the investor's beliefs, the stock prices across the three dates are

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

The stock price dynamics imply that the total return variance over the two model periods is

$$\Sigma \equiv Var(p_1 - p_0) + Var(p_2 - p_1) = \frac{\beta^2}{\tau_u} + \Sigma_v \text{ with } \Sigma_v = \frac{1}{\tau_v} + \frac{2\phi(\phi-1)\tau_{s,v}}{(\tau_v + \phi\tau_{s,v})^2}.$$

There are two major parts in the total return variance. The first part, β^2/τ_u, represents the return variance related to the market factor, and, as discussed earlier, is equal to the stock's market-factor uncertainty. The second part, Σ_v, represents the return variance related to the firm-specific factor. Σ_v equals the stock's firm-specific uncertainty, $1/\tau_v$, plus another term related to the investor's biased reaction parameter ϕ. If the investor has unbiased reactions ($\phi = 1$), Σ_v is equal to the firm-specific uncertainty; if the investor overreacts ($\phi > 1$), Σ_v increases with ϕ; if the investor underreacts ($\phi < 1$), Σ_v is non-monotonic with ϕ but increases with ϕ in the area around $\phi = 1$.

The fraction of the stock's return variance explained by the market factor determines the stock's return R^2:

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

In the presence of biased reactions to information, the return R^2 now depends on the precision of the investor's firm-specific information. In particular, R^2 decreases with $\tau_{s,v}$ if $\phi > 1$ and $\tau_v > \phi\tau_{s,v}$ or if $\phi < 1$ and $\tau_v < \phi\tau_{s,v}$.

In the meantime, biased reactions also introduce inefficiency into the stock price dynamics, which can be measured with return serial correlations:

$$\Omega = Cov\left(p_1 - p_0, p_2 - p_1\right) = Cov\left(\frac{\phi\tau_{s,v}}{\tau_v + \phi\tau_{s,v}} s_v, v - \frac{\phi\tau_{s,v}}{\tau_v + \phi\tau_{s,v}} s_v\right) = \frac{\phi(1-\phi)\tau_{s,v}}{(\tau_v + \phi\tau_{s,v})^2}. \tag{2}$$

The serial correlation is positive if $\phi < 1$ (i.e., underreaction leads to price momentum) and is negative if $\phi > 1$ (i.e., overreaction leads to price reversal.) By substituting equation (2) into (1), we obtain

$$R^2 = \frac{\frac{\beta^2}{\tau_u}}{\frac{\beta^2}{\tau_u} + \frac{1}{\tau_v} - 2\Omega}.$$

This equation shows that the stock's return R^2 can be related to the price momentum or reversal if the investor under- or over-reacts to his firm-specific information. Using return serial correlation as a measure of market inefficiency, we obtain the following properties of the stock's return R^2:

Proposition 2. *If the investor under-reacts to his firm-specific information, the stock's return R^2 is positively correlated with its price momentum; if the investor over-reacts to his firm-specific information, the stock's return R^2 is negatively correlated with its price reversal (i.e., $|\Omega|$).*

2.3 Continued Investor Overreactions

A large branch of empirical literature following the pioneer work of Jegadeesh and Titman (1993) shows that across many stock markets in the U.S. and other countries, stock returns exhibit both medium-term price momentum and long-term price reversals. The setting considered in Section 2.2 generates either price momentum or reversal, but not both, which makes it an inadequate explanation for the empirical pattern of stock returns. Daniel, Hirshleifer, and Subrahmanyam (1998, hereafter DHS) highlight the need to account for time-varying investor overreactions to generate both the medium-term momentum and long-term reversals. Specifically, they show that self-attribution bias can cause investors to become more overconfident about their private information if a public signal confirms their private information, but their confidence remains unchanged otherwise. As a result, price momentum emerges when investors further over-react to their private information after a confirming public signal. The stock price eventually reverts back as overreaction get corrected in the long run.

To examine the relation of return R^2 to medium-term momentum and long-term reversal, we incorporate the spirit of the DHS model by adding an additional date $t = 1.5$ to the setting discussed in Section 2.2. Suppose that the representative investor initially holds an unbiased assessment of his own signal s_v at $t = 1$. He updates his assessment of the precision of s_v at $t = 1.5$ depending on a public announcement θ. The announcement can be either 1 or -1 with equal probability. If $\theta = 1$, the investor overreacts and updates his assessment of the precision of s_v by a factor of $\phi > 1$; if $\theta = -1$, he regards the announcement as noise and maintains his initial assessment. The parameter ϕ measures the investor's continued overreaction.

In the original model of Daniel, Hirshleifer, and Subrahmanyam (1998), a representative investor updates his assessment of the precision of his private information based on whether the realization of a public signal confirms his private information. Here, we simplify the setting by making θ independent of the investor's private information. This assumption simplifies the analysis while preserving the key feature—that the investor's continued overreaction can lead to medium-term price momentum and long-run price reversals.

The investor's belief about v at $t = 1$ is

$$E(v|s_v) = \frac{\tau_{s,v}}{\tau_v + \tau_{s,v}} s_v,$$

and at $t = 1.5$ is

$$E(v|s_v, \theta) = \begin{cases} \frac{\phi\tau_{s,v}}{\tau_v+\phi\tau_{s,v}} s_v & \text{if } \theta = 1 \\ \frac{\tau_{s,v}}{\tau_v+\tau_{s,v}} s_v & \text{if } \theta = -1 \end{cases}.$$

Thus, the stock prices across the different dates are

$$\begin{aligned} p_0 &= 0, \\ p_1 &= \beta E(u|s_u) + E(v|s_v) = \beta \frac{\tau_{s,u}}{\tau_u + \tau_{s,u}} s_u + \frac{\tau_{s,v}}{\tau_v + \tau_{s,v}} s_v, \\ p_{1.5} &= \beta E(u|s_u) + E(v|s_v, \theta) = \beta \frac{\tau_{s,u}}{\tau_u + \tau_{s,u}} s_u + \begin{cases} \frac{\phi\tau_{s,v}}{\tau_v + \phi\tau_{s,v}} s_v & \text{if } \theta = 1 \\ \frac{\tau_{s,v}}{\tau_v + \tau_{s,v}} s_v & \text{if } \theta = -1 \end{cases}, \\ p_2 &= \beta u + v. \end{aligned}$$

Based on the derived stock price dynamics, the total return variance over the three model periods is

$$\Sigma = Var(p_1 - p_0) + Var\left(p_{1.5} - p_1\right) + Var(p_2 - p_{1.5}) = \frac{\beta^2}{\tau_u} + \Sigma_v$$

with

$$\Sigma_v = \frac{1}{\tau_v} + \frac{1}{2}\frac{1}{\tau_v}\left\{\frac{1}{\left(\tau_v + \phi\tau_{s,v}\right)^2}\left[2\left(\phi^2 - \phi\right)\tau_{s,v}\tau_v + \tau_v^2 - \phi^2\tau_{s,v}^2\right] + \frac{1}{\left(\tau_v + \tau_{s,v}\right)^2}\left(\tau_{s,v}^2 - \tau_v^2\right)\right\}.$$

The fraction of the total return variance explained by the market factor, i.e., return R^2, is

$$R^2 = \frac{\frac{\beta^2}{\tau_u}}{\Sigma} = \frac{\frac{\beta^2}{\tau_u}}{\frac{\beta^2}{\tau_u} + \Sigma_v}.$$

Note that the return R^2 is inversely related to Σ_v, the return variance related to the firm-specific factor v. One can directly verify that

$$\frac{\partial \Sigma_v}{\partial \phi} \propto 4\left(\phi - 1\right)\tau_v^2,$$

which is larger than zero if $\phi > 1$. This implies that continued investor overreaction to firm-specific information leads to a smaller return R^2.

The serial covariance of the stock returns across the first two periods is

$$\Omega = Cov\left(p_1 - p_0, p_{1.5} - p_1\right) = \frac{1}{2\tau_v}\left(\frac{\phi\tau_{s,v}}{\tau_v + \phi\tau_{s,v}} - \frac{\tau_{s,v}}{\tau_v + \tau_{s,v}}\right).$$

Note that if $\phi = 1$, $\Omega = 0$ (i.e., there is no price momentum.) Furthermore,

$$\frac{\partial \Omega}{\partial \phi} \propto \frac{\tau_{s,v}\tau_v}{\left(\tau_v + \phi\tau_{s,v}\right)^2} > 0.$$

Thus, if $\phi > 1$, $\Omega > 0$. In other words, continued investor overreaction leads to a positive serial covariance in the first two periods, which captures the medium-term price momentum widely observed in individual stock returns. As investor overreaction is eventually corrected at $t = 2$, continued investor overreaction also leads to long-term price reversal.

Consider a cross-section of stocks with different coefficients of continued investor overreactions (ϕ). The following proposition relates each stock's return R^2 to its medium-term price momentum and long-term price reversal.

Proposition 3. *With continued investor overreactions, Return R^2 is negatively related to both medium-term price momentum and long-term price reversal.*

2.4 Empirical Implications

The three settings examined in Section 2 thus far demonstrate that the claim that a stock's return R^2 is inversely related to its price efficiency cannot be substantiated by theory. We show that if the representative investor rationally reacts to available information, the return R^2 is independent of the amount of information available and thus the stock's price efficiency. If the representative investor has biased reactions to information, lower return R^2 captures market inefficiency due to investor sentiment rather than market efficiency. In fact, several empirical studies (e.g., Chan and Hameed, 2006; Kelly, 2007; Ashbaugh-Skaife, Gassen, and LaFond, 2006; Griffin, Kelly, and Nadari, 2010; Teoh, Yang and Zhang, 2007; Dasgupta, Gan, and Gao, 2010; and Bartram, Brown and Stulz, 2012) find evidence that challenges lower return R^2 as a measure of market efficiency. In particular, Kelly (2007) and Chan and Hameed (2006) show that stocks with lower R^2 tend to be smaller and have lower institutional ownership, analyst coverage and liquidity—signs inconsistent with the argument that lower R^2 corresponds to higher information efficiency. These findings are, however, consistent with our last model setting in the sense that these stocks tend to have a larger retail-investor clientele, which is more likely to display investor overreactions. The last model setting is also consistent with Brandt, et al. (2010), who show that idiosyncratic volatility is associated with speculative trading of retail investors.

In particular, Proposition 3 shows that with continued investor overreactions to firm-specific information, low return R^2 is associated with more pronounced medium-term price momentum and long-term price reversal, two widely documented anomalies. This implication is in sharp contrast to the argument put forth by MYY (2000) and subsequent papers. Our empirical analysis focuses on testing this implication.

3 Empirical Analysis

In this section, we empirically analyze the relationship of return R^2 with medium-term price momentum and long-term price reversals, first in the U.S. stock return data and then in return data of a set of international countries.

3.1 Analysis of U.S. Stock Returns

Our sample includes all NYSE/AMEX/NASDAQ listed securities on the Center for Research in Security Prices (CRSP) data files with share codes 10 or 11 (we exclude ADRs, closed-end funds, and REITs) from July 1963 to December 2011. To enter our sample, we require firms to have at least 24 monthly returns and 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. "Book equity" is defined as stockholder's equity (or common equity plus preferred stock par value, or asset minus liabilities), minus preferred stock (liquidating value, or redemption value, or par value), plus balance sheet deferred taxes and investment tax credit, if available, minus post retirement asset, if available. "Earnings" are earnings before interest, which is income before extraordinary items plus interest expense plus income statement deferred taxes, when available. "Asset" is total asset. "Firm size" (*Size*) is measured by multiplying the 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 use monthly returns to measure each stock's return R^2. More specifically, we follow

Roll (1988), Durnev, *et al.* (2003) and Durnev, *et al.* (2004) in estimating a regression of each stock's monthly returns on the contemporaneous returns of the market portfolio as well as on the industry portfolio (based on the 48 industries defined on Kenneth French's website) to which the stock belongs:

$$r_{i,t} = \alpha_{i,t} + \beta_i r_{m,t} + \gamma_i r_{I,t} + \epsilon_{i,t} \tag{3}$$

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 month t. We require a minimum of 24 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 (3) 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 four R^2 measures that differ either in estimation sample period or in whether they adjust for degrees of freedom in estimating regression (3). R^2_{PS} is the R^2 estimated using monthly returns over the entire past sample. The mean of this variable is 0.22 and the median is 0.20, with 25% of the stocks having an R^2 value less than 0.10 and 25% of the stocks having an R^2 value greater than 0.33. R^2_{FS} is estimated using the full sample of monthly returns. Its mean and median are 0.20 and 0.17, respectively. $adj.R^2_{PS}$ and $adj.R^2_{FS}$ are the corresponding R^2 measures adjusted for degrees of freedom. 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 0.99 to 1. The correlations between R^2_{PS} and R^2_{FS} and between $adj.R^2_{PS}$ and $adj.R^2_{FS}$ are also large and statistically significant, with both equal to 0.83.

Due to noise in individual stocks' monthly returns, the R^2 measures from regression (3) 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 the relationship between return R^2 and price momentum and reversals, we use R^2_{FS}, the full sample R^2 measure, as our main measure. The results from using the past-sample R^2, as well as all the adjusted R^2s, are similar and are available upon request.

Table 2 reports the performance of 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 R^2_{FS} using NYSE breakpoints and placed into quintile portfolios. Within each R^2 quintile, stocks are further sorted into quintiles based on their past twelve month return (skipping the most recent month).[2] The value-weighted returns on these double-sorted portfolios are computed over various holding periods and are reported in Panels A-E. The time series averages of the 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.[3]

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 are first sorted into size deciles, based on NYSE breakpoints, and then within each size decile further sorted into book-to-market deciles also 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.

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

[3] For robustness, we have also analyzed R^2-based momentum profits based on independently sorted momentum portfolios and equal-weighted portfolio returns. The results are similar and are available upon request.

Panel A reports average returns of momentum portfolios over the following month (month t). 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 155 basis points per month with a t-statistic of 5.50. This return spread falls steadily as R^2_{FS} increases. In the highest R^2_{FS} quintile, the return spread drops to an insignificant 39 basis points per month (t-statistic=1.25). The differences across R^2 quintiles are highly significant: the test of the hypothesis that the average momentum profit is the same between the lowest and the highest R^2 quintiles produces a t-statistic of 4.24, indicating a rejection at the one-percent significance level. The negative and significant relationship between return R^2 and momentum profits demonstrated here is clearly consistent with Proposition 3.

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. 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 148 basis points (t-statistic=6.89) in R^2_{FS} quintile 1 to an insignificant 27 basis points (t-statistic=1.15) in R^2_{FS} quintile 5. The t-statistic for the null of equal characteristic-adjusted momentum profit between R^2 quintiles 1 and 5 is 5.00 and is significant at the one-percent level. 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.

Panels B-E employ the same portfolio formation period as Panel A 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. Panel B shows that for the first six months after portfolio formation, the negative relationship between R^2 and price momentum profits remains. The raw momentum profit decreases from 104 basis points per month (t-statistic=4.19) in the lowest R^2 quintile to 38 basis points per month (t-statistic=1.46) in the highest, and the difference between the two extreme quintiles is significant at the one-percent level (t-statistic=2.63). The size and book-to-market adjusted momentum profit follows a similar pattern, decreasing from 109 basis points per month (t-statistic=6.20) to 31 basis points per month (t-statistic=1.65), with a t-statistic of 3.65 for the difference between the two extreme quintiles. 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.

Panel D reports momentum profits from two years 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), which indicate reversals of momentum profits. This 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, that they tend to dissipate after six months, and that they eventually reverse at longer horizons. In addition, the return reversals tend to be stronger in lower R^2 quintiles than in higher R^2 quintiles. For example, the average characteristic-adjusted return spread in the lowest R^2 quintile is a significant -36 basis points per month (t-statistic=-3.45) whereas it is only -16 basis points per month (t-statistic=-1.55) in the highest R^2 quintile. However, the difference between the two extreme quintiles is insignificant (t-statistic=1.49).

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 four years to five years after portfolio formation. Again, the reversals are strongest in the lowest R^2 quintile (-42 basis points per month with a t-statistic of -3.22 in raw returns and -22 basis points per month with a t-statistic of -2.17 in characteristic-adjusted returns) and diminish gradually as R^2 increases. There is no evidence of reversals in the highest R^2 quintile (1 basis point per month with a t-statistic of 0.13 in raw returns and 8 basis points per month with a t-statistic of 0.93 in characteristic-adjusted returns). Moreover, the difference between the two extreme quintiles is highly significant (t-statistics of 2.90 and 2.41 in raw and characteristic-adjusted returns, respectively).

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 of Table2 – that the momentum profits across all five R^2 quintiles tend to reverse at longer horizons and that the reversal tends to be stronger for lower R^2 quintiles. This pattern is again consistent with Proposition 3 regarding the negative relationship between return R^2 and long-term price reversal.

3.2 Analysis of International Stock Returns

In this subsection, we study the relationship between country-level return R^2 and price momentum profits using a set of countries that include those originally investigated by MYY.[4] Our sample, provided by Datastream, includes publicly traded firms from 47 developed and emerging countries from July 1981 to December 2010.[5] To enter our analysis, a firm must have had a minimum of 24 monthly returns during the sample period. In order to minimize potential biases arising from low-price and illiquid stocks, we drop stocks that are in the bottom 10 percent in terms of stock price from each country. In addition, we apply several screening procedures for monthly returns as set forth in Ince and Porter (2006) and Hou, Karolyi, and Kho (2011). First, any return above 300% that is reversed within one month is treated as missing. Second, to exclude remaining outliers that cannot be identified as stock splits or mergers, we also treat as missing the monthly returns that fall outside the 0.1% and 99.9% range for each country.

We estimate country-specific momentum profits at the beginning of each month by sorting the qualifying stocks in each country into quintile portfolios based on their cumulative raw return over the past six months (skipping the most recent month), following Griffin, Ji, and Martin (2003) and Hou, Karolyi, and Kho (2011). Value-weighted returns on those quintile

[4] We have also studied the cross-country relationship between return R^2 and long-term price reversals. However, due to the noise in international return data, we are not able to obtain significant results. They are available upon request.

[5] The list of countries includes Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Cyprus, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Romania, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, United States, and Venezuela. The specific starting date varies by country and is reported in Table 3.

portfolios as well as the spread between the extreme quintiles are calculated each month. To estimate country-level R^2, for each country in our sample, we follow MYY and regress the full sample of monthly returns of each firm on the local market index (excluding the firm itself) and the U.S. market index to obtain the return R^2 for each firm. We then aggregate the firm-level R^2 to the country level using the sum of squared total variations for each firm as the weight. The main difference between our approach and MYY's is that we use the full sample of monthly returns to estimate the firm-specific R^2 whereas MYY use the bi-weekly returns in 1995 to estimate firm-specific R^2.

Panel A of Table 3 reports, for each country in our sample, the full-sample R^2 (R^2_{FS}), the average value-weighted 5-1 momentum profit as well as its t-statistic, the start date of each country, and the average number of firms. Countries are ranked by R^2_{FS}. For comparison purposes, we also report the original R^2 from MYY, R^2_{MYY}, copied verbatim from their Table 2.

The panel shows substantial variations in R^2 across countries. For example, R^2_{FS} ranges from as low as 0.0449 (Peru) to as high as 0.4416 (China). By comparison, R^2_{MYY} shows slightly greater variation, ranging from a low of 0.0210 (U.S.) to a high of 0.5690 (Poland). The momentum profits also vary significantly across countries, consistent with the findings of Griffin, Ji, and Martin (2003) and Hou, Karolyi, and Kho (2011). They range from a low of -111 basis points per month (t-statistic=-1.05) in Indonesia to a high of 218 basis points per month (t-statistic of 2.49) in Ireland.

More important, Table 3 Panel A also shows that countries with lower return R^2 tend to have more pronounced price momentum than countries with higher R^2. Among the ten countries with the lowest R^2_{FS}, six of them (Hungary, Canada, Ireland, Israel, Australia, and New Zealand) produce highly significant momentum profits, ranging from 129 (t-statistic=2.83, Canada) to 218 (t-statistic=2.49, Ireland) basis points per month. On the other hand, the ten countries with the highest R^2_{FS} produce momentum profits ranging from -58 (t-statistic=-0.77, China) to 68 (t-statistic=1.01, Greece) basis points per month, none of which is statistically significant.

Panel B of Table 3 reports the cross-country correlations between R^2 and average momentum profits. The correlation between R^2_{FS} and average momentum profits is -0.36 and highly significant. The correlation between R^2_{MYY} and average momentum profits is even higher at -0.53.[6]

To formally test the relation between country-level return R^2 and price momentum profits, in Panel C of Table 3 we report the regression results from regressing the average 5-1 momentum profits on R^2_{FS} and R^2_{MYY} separately. The coefficient on R^2_{FS} is -0.0305 with a t-statistic of -2.57, which is consistent with aforementioned negative correlation between R^2 and momentum profits. In addition, the cross-country variation in R^2_{FS} captures 11% of the variation in momentum profits. Regressing momentum profits on R^2_{MYY} also produces a negative and significant coefficient (-0.0326 with a t-statistic of -3.79). Interestingly, R^2_{MYY} seems to explain a much larger fraction (27%) of the cross-country variation in momentum profits. Finally, Figure 2 presents the scatter plots of country-level momentum profits against country-level return R^2 with the regression lines also being plotted. The negative relation between momentum profits and R^2 is fairly evident from the plots.

In sum, the results in Table 3 and Figure 2 suggest higher price momentum profits in low R^2 countries. This cross-country analysis of R^2 and price momentum complements the U.S. evidence and provides further support to Proposition 3.

4 Conclusion

Our analysis casts doubt on the argument that low return R^2 is a measure of market efficiency. From the theoretical perspective, the use of this measure builds on the premise that idiosyncratic return fluctuations reflects stock-specific information about asset fundamentals. However, in a standard rational expectations model, we show that the link between return R^2 and the amount of firm-specific information does not exist. Instead, we argue that return R^2 can actually reflect investor sentiment and market inefficiency. Using an alternative model in which the investor has continued overreaction to firm-specific information, we show that lower return R^2 is associated with more pronounced medium-term price momentum and long-term price reversal. Our empirical evidence supports this implication across different stocks traded in the U.S and across stock markets in a set of international countries. Our

[6] The correlation between R^2_{FS} and R^2_{MYY} is 0.63.

analysis thus cautions against the use of return R^2 as a measure of market efficiency.

Our findings suggest that previously documented properties of low R^2 stocks might be caused by investor sentiment instead of firm-specific information. For example, the finding that 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 reflect firm managers' reactions to investor sentiment, instead of value-relevant information in stock prices.

References

Ashbaugh-Skaife, H. , J. Gassen and R. LaFond (2006), Does stock price synchronicity represent firm-specific information? The international evidence, Working paper, Columbia Univerisity.

Barberis, Nicholas and Richard Thaler (2003), A survey of behavioral finance, In: Constantinides, G., Harris, M., Stulz, R. (Eds.), *Handbook of the Economics of Finance*, North-Holland, Amsterdam.

Bartram, Söhnke, Gregory Brown and Rene Stulz (2012), Why are U.S. stocks more volatile?, *Journal of Finance* 67, 1329-1370.

Brandt, Michael, Alon Brav, John R. Graham, and Alok Kumar (2010), The idiosyncratic volatility puzzle: time trend or speculative episodes? *Review of Financial Studies* 23, 863-899.

Campbell, John, Martin Lettau, Burton Malkiel, and Xu Yexiao (2001), Have individual stock returns become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 11-43.

Chan, K and A. Hameed (2006), Stock price synchronicity and analyst coverage in emerging markets, *Journal of Financial Economics* 80, 115-147.

Chen, Qi, Itay Goldstein and Wei Jiang (2006), Price informativeness and investment sensitivity to stock prices, *Review of Financial Studies* 18, 289-324.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russell Wermers (1997), Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

Daniel, Kent, David Hirshleifer and Avanidhar Subrahmanyam (1998), Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839-1885.

Dasgupta, Sudipto, Jie Gan, and Ning Gao (2010), Transparency, price informativeness, and stock return synchronicity: Theory and evidence, *Journal of Financial and Quantitative Analysis* 45, 1189-1220.

Durnev, Artyom, Randall Morck, Bernard Yeung, and Paul Zarowin (2003), Does greater firm-specific return variation mean more or less informed stock pricing? *Journal of Accounting Research* 41, 797-836.

Durnev, Artyom, Randall Morck, and Bernard Yeung (2004), Does firm-specific information in stock prices guide capital budgeting? *Journal of Finance* 59, 65-105.

Fama, Eugene and Kenneth R. French (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Griffin, John M., Xiuqing Ji, and J. Spencer Martin (2003), Momentum investing and business cycle risk: Evidence from pole to pole, *Journal of Finance* 58, 2515-2547.

Griffin, John M., Patrick J. Kelly, and Federico Nadari (2010), Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets, *Review of Financial Studies* 23, 3225-3277.

Hirshleifer, David (2001), Investor psychology and asset pricing, *Journal of Finance* 56, 1533-1597.

Hou, Kewei, Andrew Karolyi, and Bong Chan Kho (2011), What fundamental factors drive global stock returns?, *Review of Financial Studies* 24, 2527-2574.

Ince, Ozgur and Burt Porter (2006), Individual equity return data from Thomson Datastream: Handle with care!, *Journal of Financial Research* 29, 463-479.

Jegadeesh, Narasimhan, and Sheridan Titman (1993), Returns to buying winners and selling losers: Implication for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan and Sheridan Titman (2001), Profitability of momentum strategies: An evaluation of laternative explanations, *Journal of Finance* 56, 699-720.

Jin, Li and Stewart C. Myers (2006), R2 around the world: new theory and new tests, Journal of Financial Economics 79(2), 257-292.

Kelly, Patrick (2007), Information efficiency and firm-specific return variation, Working paper, Arizona State University.

Lee, Charles, and Bhaskaran Swaminathan (2000), Price momentum and trading volume, *Journal of Finance* 55, 2017-2069.

Morck, Randall, Bernard Yeung, and Wayne Yu (2000), The information content of stock markets: Why do emerging markets have synchronous stock Price movements? *Journal of Financial Economics* 58, 215-260.

Roll, Richard (1988), R^2, *Journal of Finance* 43, 541-566.

Ross, Stephen (1989), Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy, *Journal of Finance* 44, 1-17.

Shiller, R. J. (1981), Do stock prices move too much to be justified by subsequent changes in dividends?, American Economic Review 71, 421-436.

Teoh, Siew Hong, Yong Yang and Yinglei Zhang (2007), R-squared: Noise or firm-specific information, Working paper, University of California, Irvine.

Wurgler, Jeffrey (2000), Financial markets and the allocation of capital, *Journal of Financial Economics* 58, 187-214.

West, Kenneth (1988), Dividend innovations and stock price volatility, *Econometrica* 56, 37-61.

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_{PS} and R^2_{FS} are the R^2 estimated from the entire past sample and the full sample of monthly return data, respectively. *adj.* R^2_{PS} and *adj.* R^2_{FS} are the corresponding adjusted R^2 measures. We use ***, ** and * to 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_{PS}	0.22	0.15	0.60	-0.33	0.10	0.20	0.33	1876711
R^2_{FS}	0.20	0.14	0.73	-0.08	0.08	0.17	0.29	2137437
adj. R^2_{PS}	0.20	0.16	0.55	-0.38	0.07	0.18	0.31	1876711
adj. R^2_{FS}	0.18	0.14	0.69	-0.13	0.07	0.16	0.28	2137437

Panel B. Correlations

	R^2_{PS}	R^2_{FS}	*adj.* R^2_{PS}	*adj.* R^2_{FS}
R^2_{PS}	1.00 ***			
R^2_{FS}	0.83 ***	1.00 ***		
adj. R^2_{PS}	0.99 ***	0.83 ***	1.00 ***	
adj. R^2_{FS}	0.83 ***	1.00 ***	0.83 ***	1.00 ***

Table 2. Performance of R^2-Sorted Portfolios over Different Horizons

Average monthly raw and characteristic-adjusted returns on portfolios sorted by the full-sample R^2 (R^2_{FS}) and cumulative raw return over different sorting periods are reported over the period from July 1965 to December 2011 for various holding periods. At the beginning of each month, stocks are ranked by R^2_{FS} using NYSE breakpoints and placed into quintiles (quintile 1 being the lowest and 5 being the highest). Within each R^2 quintile, stocks are then sorted into quintiles based on the return of the specified sorting periods (quintile 1 contains the past losers and quintile 5 contains the past winners). 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 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: Sorting Period=t-12:t-2, 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	-0.0027	0.0032	0.0061	0.0093	0.0128	**0.0155**	RSQ1	-0.0118	-0.0063	-0.0035	-0.0002	0.0030	**0.0148**
	-0.80	*1.34*	*3.04*	*4.44*	*4.68*	*5.50*		*-7.35*	*-6.16*	*-3.87*	*-0.20*	*2.53*	*6.89*
2	0.0032	0.0070	0.0089	0.0110	0.0127	**0.0095**	2	-0.0061	-0.0021	-0.0008	0.0012	0.0023	**0.0084**
	0.89	*3.04*	*4.24*	*5.21*	*4.46*	*3.10*		*-3.58*	*-2.16*	*-0.89*	*1.45*	*1.81*	*3.58*
3	0.0066	0.0072	0.0097	0.0106	0.0151	**0.0084**	3	-0.0037	-0.0012	0.0011	0.0011	0.0049	**0.0086**
	1.94	*3.09*	*4.74*	*4.90*	*5.52*	*2.82*		*-2.20*	*-1.45*	*1.36*	*1.25*	*4.35*	*3.78*
4	0.0094	0.0086	0.0074	0.0108	0.0147	**0.0053**	4	0.0002	0.0001	-0.0015	0.0013	0.0052	**0.0050**
	3.03	*3.79*	*3.54*	*4.92*	*5.33*	*1.83*		*0.15*	*0.18*	*-2.09*	*1.67*	*4.17*	*2.32*
RSQ5	0.0092	0.0092	0.0090	0.0103	0.0131	**0.0039**	RSQ5	0.0008	0.0005	-0.0003	0.0015	0.0035	**0.0027**
	2.87	*3.96*	*4.33*	*4.84*	*4.74*	*1.25*		*0.49*	*0.69*	*-0.44*	*2.06*	*2.63*	*1.15*

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	0.0000	0.0042	0.0073	0.0086	0.0104	**0.0104**	RSQ1	-0.0099	-0.0056	-0.0026	-0.0008	0.0010	**0.0109**
	0.00	*1.79*	*3.72*	*4.18*	*3.95*	*4.19*		*-7.32*	*-6.45*	*-3.64*	*-1.05*	*1.00*	*6.20*
2	0.0042	0.0065	0.0091	0.0104	0.0116	**0.0074**	2	-0.0055	-0.0029	-0.0008	0.0007	0.0020	**0.0075**
	1.22	*2.87*	*4.53*	*5.10*	*4.18*	*2.61*		*-3.27*	*-3.59*	*-1.09*	*0.96*	*1.94*	*3.55*
3	0.0071	0.0084	0.0094	0.0105	0.0129	**0.0057**	3	-0.0024	-0.0007	0.0002	0.0013	0.0035	**0.0059**
	2.26	*3.70*	*4.70*	*5.03*	*4.72*	*2.23*		*-1.54*	*-0.95*	*0.34*	*2.06*	*3.77*	*3.04*
4	0.0085	0.0082	0.0087	0.0101	0.0133	**0.0048**	4	-0.0010	-0.0005	0.0001	0.0010	0.0039	**0.0049**
	2.95	*3.78*	*4.30*	*4.81*	*4.75*	*1.91*		*-0.85*	*-0.73*	*0.14*	*1.68*	*3.48*	*2.73*
RSQ5	0.0086	0.0089	0.0094	0.0099	0.0124	**0.0038**	RSQ5	0.0000	0.0000	0.0006	0.0010	0.0031	**0.0031**
	2.91	*4.02*	*4.74*	*4.77*	*4.57*	*1.46*		*-0.02*	*-0.02*	*1.23*	*1.85*	*2.70*	*1.65*

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	0.0033	0.0057	0.0079	0.0077	0.0075	**0.0042**	RSQ1	-0.0073	-0.0044	-0.0023	-0.0017	-0.0016	**0.0057**
	1.10	*2.53*	*4.07*	*3.76*	*2.97*	*1.95*		*-5.85*	*-5.93*	*-3.36*	*-2.18*	*-1.98*	*3.85*
2	0.0067	0.0074	0.0086	0.0099	0.0098	**0.0032**	2	-0.0036	-0.0022	-0.0011	0.0002	0.0007	**0.0043**
	1.97	*3.25*	*4.27*	*4.91*	*3.65*	*1.19*		*-2.10*	*-2.80*	*-1.76*	*0.39*	*0.79*	*2.13*
3	0.0091	0.0089	0.0096	0.0099	0.0120	**0.0030**	3	-0.0007	-0.0007	0.0003	0.0009	0.0026	**0.0033**
	3.00	*4.09*	*4.87*	*4.78*	*4.42*	*1.33*		*-0.52*	*-1.02*	*0.54*	*1.61*	*3.15*	*2.06*
4	0.0092	0.0089	0.0090	0.0100	0.0121	**0.0029**	4	-0.0005	-0.0002	0.0002	0.0013	0.0028	**0.0033**
	3.39	*4.17*	*4.52*	*4.78*	*4.34*	*1.34*		*-0.53*	*-0.40*	*0.51*	*2.48*	*2.84*	*2.23*
RSQ5	0.0093	0.0094	0.0095	0.0092	0.0114	**0.0020**	RSQ5	0.0004	0.0005	0.0007	0.0005	0.0023	**0.0019**
	3.28	*4.32*	*4.81*	*4.50*	*4.24*	*0.87*		*0.39*	*0.74*	*1.40*	*1.23*	*2.25*	*1.13*

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	0.0104	0.0089	0.0092	0.0078	0.0050	**-0.0053**	RSQ1	-0.0008	-0.0018	-0.0015	-0.0025	-0.0044	**-0.0036**
	3.75	*4.23*	*4.76*	*3.80*	*2.02*	*-3.66*		*-0.82*	*-2.45*	*-2.12*	*-3.51*	*-5.15*	*-3.45*
2	0.0104	0.0101	0.0100	0.0096	0.0090	**-0.0014**	2	-0.0005	-0.0004	-0.0007	-0.0006	-0.0008	**-0.0003**
	3.98	*4.45*	*3.96*	*4.59*	*3.52*	*-1.00*		*-0.60*	*-0.42*	*-0.51*	*-0.91*	*-1.07*	*-0.26*
3	0.0124	0.0101	0.0097	0.0099	0.0109	**-0.0015**	3	0.0015	0.0001	0.0002	0.0006	0.0013	**-0.0002**
	4.83	*5.08*	*5.03*	*4.82*	*4.03*	*-1.08*		*1.92*	*0.13*	*0.26*	*1.07*	*1.58*	*-0.19*
4	0.0125	0.0101	0.0097	0.0094	0.0105	**-0.0020**	4	0.0023	0.0007	0.0006	0.0004	0.0014	**-0.0009**
	5.15	*5.07*	*5.04*	*4.58*	*3.83*	*-1.48*		*2.98*	*1.31*	*1.21*	*0.96*	*1.44*	*-0.90*
RSQ5	0.0124	0.0099	0.0098	0.0093	0.0097	**-0.0027**	RSQ5	0.0027	0.0007	0.0008	0.0007	0.0011	**-0.0016**
	5.25	*4.83*	*4.94*	*4.53*	*3.81*	*-1.95*		*3.56*	*1.31*	*1.66*	*1.56*	*1.29*	*-1.55*

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	0.0119	0.0103	0.0099	0.0090	0.0077	**-0.0042**	RSQ1	0.0002	-0.0010	-0.0012	-0.0016	-0.0020	**-0.0022**
	4.54	*4.94*	*5.01*	*4.38*	*3.11*	*-3.22*		*0.19*	*-1.28*	*-1.50*	*-2.23*	*-2.52*	*-2.17*
2	0.0109	0.0102	0.0103	0.0092	0.0100	**-0.0009**	2	-0.0002	-0.0007	-0.0002	-0.0012	-0.0003	**0.0000**
	3.96	*4.26*	*4.14*	*4.38*	*3.91*	*-0.58*		*-0.19*	*-0.74*	*-0.16*	*-1.72*	*-0.38*	*-0.02*
3	0.0117	0.0101	0.0100	0.0105	0.0110	**-0.0006**	3	0.0011	-0.0003	-0.0001	0.0006	0.0016	**0.0005**
	4.84	*5.10*	*5.23*	*5.19*	*4.22*	*-0.55*		*1.54*	*-0.49*	*-0.08*	*1.04*	*2.16*	*0.53*
4	0.0116	0.0103	0.0093	0.0101	0.0113	**-0.0003**	4	0.0011	0.0006	0.0001	0.0010	0.0019	**0.0008**
	5.07	*5.30*	*4.75*	*4.87*	*4.42*	*-0.29*		*1.60*	*1.17*	*0.16*	*1.93*	*2.37*	*0.85*
RSQ5	0.0107	0.0103	0.0100	0.0101	0.0109	**0.0001**	RSQ5	0.0008	0.0009	0.0008	0.0011	0.0016	**0.0008**
	5.03	*4.94*	*4.93*	*4.90*	*4.47*	*0.13*		*1.29*	*1.62*	*1.66*	*2.17*	*2.19*	*0.93*

Table 3. R^2 and Price Momentum, International Evidence

Panel A reports the country-level R^2 and momentum profits over the period from July 1981 to December 2010. Start date is the beginning date for each country. n is the average number of firms for each country. R^2_{FS} is the country-level R^2 calculated in accordance with Morck, Yeung, and Yu (2000) and by using the full sample of monthly returns. R^2_{MYY} is the original R^2 from Morck, Yeung, and Yu (2000), which is calculated using bi-weekly returns in 1995. Mom 5-1 is the average value-weighted raw return spread between momentum quintile 5 and 1 for each country. We report t-statistics in *italics*. Panel B reports the cross-country correlation between R^2 and average momentum profits. Panel C reports the results from regressing average momentum profits on R^2.

Panel A: Country-Level R^2 and Price Momentum

Country	Start date	n	R^2_{FS}	R^2_{MYY}	Mom 5-1	*t*-stat	Country	Start date	n	R^2_{FS}	R^2_{MYY}	Mom 5-1	*t*-stat
Peru	199108	71	0.0449	0.2880	-0.0027	*-0.24*	Netherlands	198107	134	0.2130	0.1030	0.0068	*1.56*
Hungary	199108	28	0.1045	.	0.0174	*2.04*	South Africa	198107	228	0.2210	0.1970	0.0110	*2.66*
Canada	198107	807	0.1057	0.0620	0.0129	*2.83*	Hong Kong	198107	340	0.2216	0.1500	0.0118	*2.64*
Ireland	198107	25	0.1216	0.0580	0.0218	*2.49*	Denmark	198107	140	0.2231	0.0750	0.0133	*3.60*
Indonesia	199011	125	0.1227	0.1400	-0.0111	*-1.05*	Austria	198107	67	0.2336	0.0930	0.0052	*1.37*
U.S.	198107	3369	0.1302	0.0210	0.0027	*0.87*	Switzerland	198107	194	0.2555	.	0.0071	*2.22*
Israel	198608	291	0.1447	.	0.0158	*2.79*	South Korea	198107	167	0.2562	0.1720	-0.0034	*-0.57*
Australia	198107	673	0.1557	0.0640	0.0182	*4.79*	Belgium	198107	107	0.2585	0.1460	0.0111	*3.14*
New Zealand	198608	47	0.1594	0.0640	0.0203	*2.66*	Cyprus	199307	63	0.2600	.	0.0105	*1.16*
Pakistan	199001	183	0.1613	0.1750	0.0081	*1.42*	Sweden	198107	232	0.2655	0.1420	0.0075	*1.39*
Brazil	199501	40	0.1636	0.1610	-0.0071	*-0.66*	Thailand	198708	282	0.2656	0.2710	0.0002	*0.03*
Philippines	198807	110	0.1650	0.1640	-0.0032	*-0.40*	Poland	199201	64	0.2673	0.5690	-0.0005	*-0.04*
Egypt	199507	78	0.1676	.	0.0188	*2.60*	Venezuela	199008	24	0.2716	.	0.0069	*0.72*
Romania	199607	39	0.1717	.	-0.0011	*-0.10*	Mexico	198808	75	0.2723	0.2900	0.0061	*1.31*
Chile	199007	88	0.1732	0.2090	0.0083	*1.51*	Japan	198107	1718	0.2934	0.2340	-0.0022	*-0.60*
Germany	198107	443	0.1742	0.1140	0.0098	*2.47*	Spain	198608	103	0.2937	0.1920	0.0036	*0.84*
Sri Lanka	198801	131	0.1821	.	0.0083	*1.57*	Greece	198808	184	0.3064	0.1920	0.0068	*1.01*
U.K.	198107	1229	0.1902	0.0620	0.0057	*1.62*	Italy	198107	198	0.3562	0.1830	0.0062	*1.82*
Finland	198708	89	0.1932	0.1420	0.0126	*2.22*	Singapore	198107	206	0.3744	0.1910	0.0012	*0.28*

Colombia	199208	41	0.1937	0.2090	0.0033	*0.50*	Turkey	198808	180	0.4096	0.3930	-0.0013	*-0.16*
France	198107	495	0.1978	0.0750	0.0048	*1.42*	Taiwan	198807	356	0.4099	0.4120	-0.0056	*-1.15*
India	198108	634	0.2017	0.1890	0.0016	*0.22*	Malaysia	198107	353	0.4193	0.4290	0.0021	*0.38*
Norway	198107	123	0.2074	0.1190	0.0102	*2.39*	China	199108	684	0.4416	0.4530	-0.0058	*-0.77*
Argentina	198907	55	0.2122	.	0.0083	*0.94*							

Panel B: Correlations

	R^2_{FS}	R^2_{MYY}	Mom 5-1
R^2_{FS}	1.00 ***		
R^2_{MYY}	0.63 ***	1.00 ***	
Mom 5-1	-0.36 ***	-0.53 ***	1.00 ***

Panel C: Regressions

Dependent Variable		Intercept	R^2_{FS}	R^2_{MYY}	adj. R^2
Mom 5-1	Coefficient	0.0129	-0.0305		0.11
	t-statistic	*4.48*	*-2.57*		
Mom 5-1	Coefficient	0.0112		-0.0326	0.27
	t-statistic	*5.77*		*-3.79*	

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).

Figure 1A: Cumulative Raw Momentum Profits

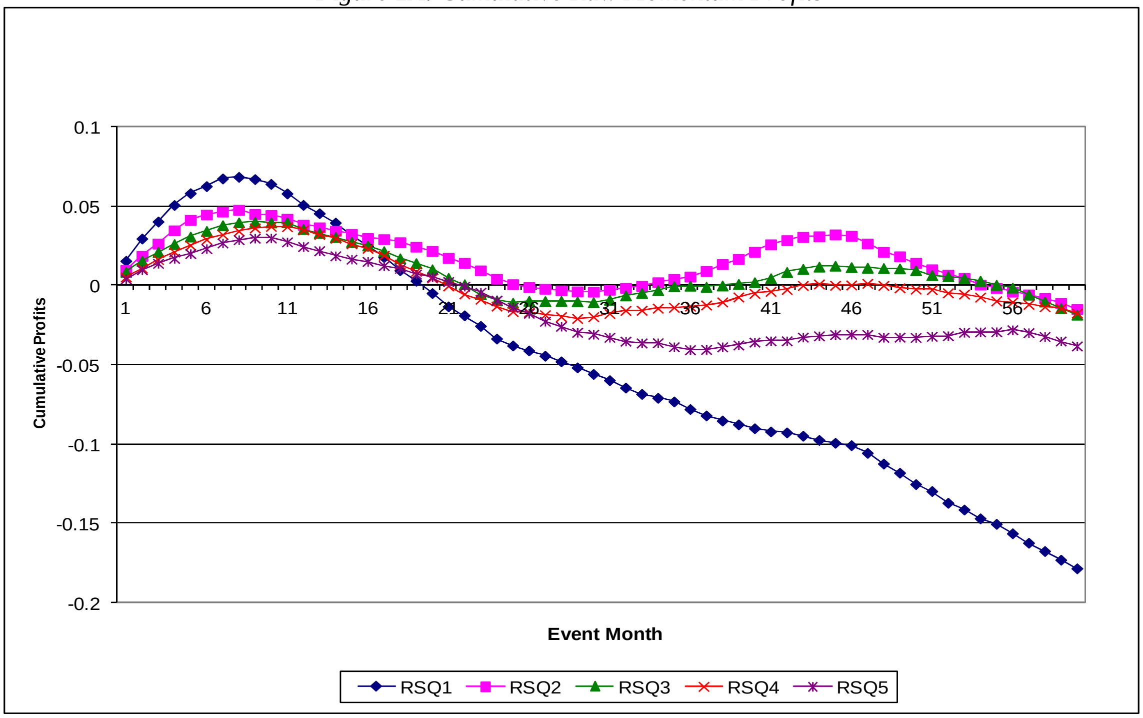

Figure 1B: Cumulative Adjusted Momentum Profits

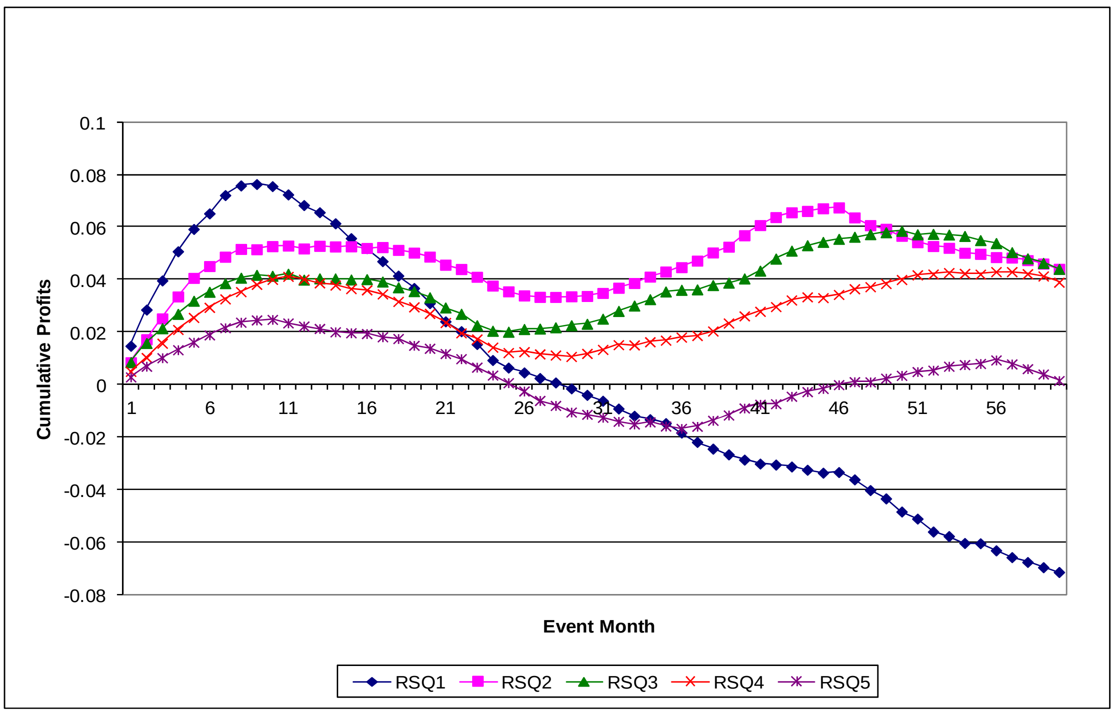

Figure 2. Country-Level R^2 and Momentum Profits

The scatter plots between country-level momentum profits and country-level R^2 are presented. Mom 5-1 is the average value-weighted raw return spread between momentum quintile 5 and 1 for each country. R^2_{FS} is the country-level R^2 calculated in accordance with Morck, Yeung, and Yu (2000) and by using the full sample of monthly returns. R^2_{MYY} is the original R^2 from Morck, Yeung, and Yu (2000), which is calculated using bi-weekly returns in 1995. The regression lines between momentum profits and R^2 are also plotted.

Figure 2A: Mom 5-1 vs. R^2_{FS}

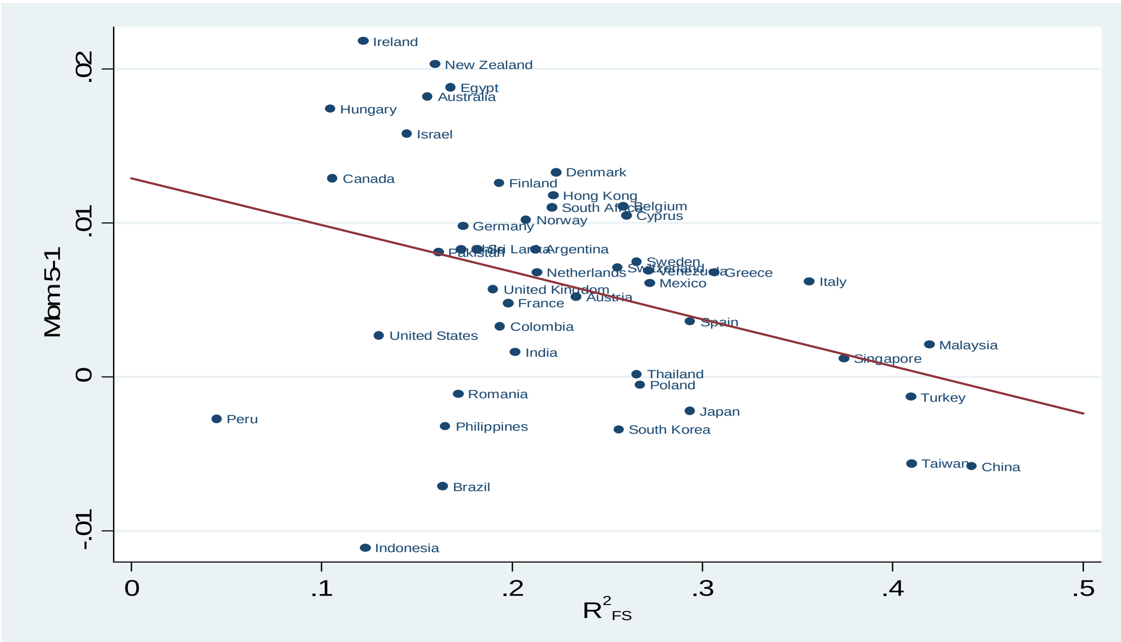

Figure 2B: Mom 5-1 vs. R^2_{MYY}