R-Square and Market Efficiency*

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R-square and Market Efficiency

Abstract

This paper addresses the debate about R-square as an indicator of information quality: Does low R-square indicate early resolution of uncertainty through the arrival of firm-specific information, or does it indicate a high level of uncertainty that remains unresolved? Tests based on the post-earnings-announcement drift, V/P, accruals, and net operating assets anomalies all reject the view that low R-square indicates a high quality information environment (early resolution of uncertainty). Low R-square firms have lower future earnings response coefficient, indicating that their current stock price incorporates a smaller amount of future earnings news, and thus more uncertainty about future earnings news remains unresolved. Furthermore, low R-square firms have worse information environment as measured by earnings quality, earnings persistence, and earnings predictability, and have higher probability of distress.

R-square and Market Efficiency

The extant literature offers contradictory views on the information implication of the R-square statistic obtained from a regression of the firm's returns on the market index or some multiple-factor returns in an asset pricing model. Following Morck, Yeung, and Yu (2000), a number of studies interpret a lower R-square as indicating that more firm-specific information is incorporated in stock prices. In other words, the firm's stock price is more efficient at capturing firm-specific information, and therefore the quality of the information environment is better. On the other hand, other studies (discussed below) question this interpretation and conclude the opposite, that the information environment of a lower R-square firm has higher uncertainty.

Intuitively, a low R-square could represent the fact that much of firm-specific uncertainty was resolved during the measurement period. Ceteris paribus, this implies low remaining uncertainty about the stock. For example, an information environment in which information is rapidly and credibly disclosed could resolve greater firm-specific uncertainty, increasing the realized historical idiosyncratic volatility. We call this possibility that low R-square represents a good information environment the *Early Resolution* (*ER*) *Hypothesis*.

However, an alternative possibility is that R-square is low when the amount of firm-specific uncertainty was high compared to other firms, implying that such uncertainty may continue to be high for this firm when compared to other firms in the future. We call this possibility the *Cross-sectional Uncertainty Variation* (*XUV*) *Hypothesis*. The presence of opposing arguments about the relation of R-square to the quality of the information environment suggests that it is useful to test empirically between alternative interpretations.

Subsequent to Durnev, Morck, Yeung and Zarowin (2003), empirical studies have provided very mixed conclusions about whether low R-square is associated with high stock price informativeness. Jin and Myers (2006) and Hutton, Marcus, and Tehranian (2009) find that R-square decreases with information transparency, whereas Hou, Lin, and Xiong (2006), Ashbaugh-Skaife, Gassen, and LaFond (2006), Kelly (2007), Bartram, Brown, and Stulz (2009), and Dasgupta, Gan, and Gao (2009) conclude the opposite.

It is important to test between these alternative interpretations because the R-square statistic (or equivalently stock price idiosyncratic volatility) has been widely used in the literature to proxy for the quality of the information environment at either the individual-firm or country level. Examples of papers that use low R-square to represent good information environment include Durnev et al. (2004), Piotroski and Roulstone (2004), Chan and Hameed (2006), Bakke and Whited (2006), and Fernandes and Ferreira (2008, 2009). Examples of papers that use the opposite implication that low R-square measures poor information environment include Ali, Hwang, and Trombley (2003), Mashruwala, Rajgopal, and Shevlin (2006), and Zhang (2006).

As Durnev et al. (2003) argue, if higher firm-specific stock return variation, or lower R-square, reflects more firm-specific information, then it is a desirable market attribute since it reflects more informationally efficient stock prices, and thus more efficient capital allocation. In this paper we test whether lower R-square is associated with higher efficient functioning of the capital markets. The stock market is said to exhibit functional efficiency if stock prices direct capital to the highest-value uses (Tobin, 1982). A necessary condition for functional stock market efficiency is that stock prices track firm fundamentals closely (Durnev et al., 2003). We investigate here the relation between R-square and four accounting-based regularities that are usually viewed as violating the efficient market hypothesis (EMH), the post-earnings-announcement drift anomaly (hereafter PEAD; Bernard and Thomas, 1990), the V/P anomaly (Lee, Myers and Swaminathan, 1998), the accrual anomaly (Sloan, 1996), and the net operating assets anomaly (Hirshleifer, Hou, Teoh and Zhang 2004).

We focus on these anomalies because an extensive theoretical and empirical literature in accounting and finance views the presence of these anomalies as indicating that stock prices are inefficient with respect to information about future cash flows that are contained in these predictive variables (earnings surprises, V/P, accruals, and net operating assets). In other words, these anomalies are, at least, partially due to the inability of investors to fully and accurately absorb the information about *future* cash flows that is contained in the available accounting measures.[1] Then if R-square is positively related to the amount of firm-specific information that has yet to be incorporated by investors either because of high inherent uncertainty or low amount of early resolution, these anomalies should be stronger among high R-square firms. In contrast, if high R-square is an indicator of low remaining firm-specific uncertainty because of high amount of early resolution or inherent low amount of firm-specific uncertainty, these anomalies should be weaker among high R-square firms. We test directly whether the firm's R-square increases with the strength of these anomalies.

Furthermore, we revisit the price informativeness tests in Durnev et al. (2003). They define price informativeness as the amount of information about future earnings that

[1] It is of course possible that fully attentive investors use all currently available information contained in these predictive variables but misinterpret the information in a biased way. For example, they may overreact to the information. In our perspective, we only consider whether information contained in the predictive variables are accurately used by investors. Our main purpose is not just to test whether the market reacts to firm-specific information, but whether it does so accurately. Whether market reactions are efficient is crucial for evaluating a literature which argues that when R-square is low, capital is allocated efficiently. Thus, in the situation just described our tests would correctly tell us that the market is not accurately incorporating firm-specific information.

current stock prices contain, or alternatively, the degree of association between current stock returns and future earnings. They argue that prices of low R-square firms are more informative about fundamentals such as earnings. Their matched-sample test severely restricts the sample to only 500 firms. Using their price informativeness measure, we employ a regression method that allows for a much larger sample of about 44,000 observations.

Because earnings information is a primary source of firm-specific information (Graham, Harvey, and Rajgopal, 2005), we extend our investigation to the relation between R-square and various earnings attributes that past accounting literature showed to be associated with firm information environment (Francis, Lafond, Ohlson, and Schipper, 2004). These earnings attributes include earnings quality (defined as in Dechow and Dichev, 2002)), persistence, predictability, and volatility. Francis et al. find that firms with less favorable earnings attributes are more likely to observe a higher cost of capital, consistent with the view that poor quality reporting hinders information dissemination between firms and investors. We use earnings quality to proxy for the amount of uncertainty in the firm. Our cross-sectional tests complement Rajgopal and Venkatachalam (2008), who test and report negative time-series association between accruals quality and firm-specific return volatilities.

Some of these earnings attributes may be interpreted as measures of uncertainty about either firm fundamentals or disclosure quality. We examine the association of R-square first with measures that are more representative of uncertainty about firm fundamentals, such as the volatility of earnings and its components and the proportion of earnings derived from accounting adjustments relative to cash flows from operations, and several distress measures, such as the incidence of losses, Altman's (1968) Z-score, and a market-based bankruptcy risk measure (Hillegeist et al., 2004). We also examine the relation of R-square with a measure of disclosure quality that directly gauges the perception of public investors, namely, the disclosure scores assessed by financial analysts as published by the Association of Investment Management Research (hereafter, AIMR scores).

Overall, our evidence does not support the *ER* hypothesis, and instead is consistent with the *XUV* hypothesis. We find that all four financial anomalies are much stronger among firms with lower R-square values. These findings suggest that stocks whose returns have low R-square may incorporate *less information about future fundamentals*, and are more difficult for investors to analyze accurately. This casts doubt upon the justification for using low R-square as a proxy for good firm-specific information environment. Our findings that, R-square is inversely related to the degree of mispricing instead suggest that R-square is a positive proxy for the quality of the information environment.

We find that firms with low R-square have lower future earnings response coefficient. This indicates that the current stock price of low R-square firms anticipates a smaller amount of future earnings information than high R-square firms. Therefore, low R-square firms have greater uncertainty that remains unresolved than high R-square firms. Our inference about R-square is bolstered by further findings that low R-square firms are characterized by low quality earnings, low persistence, low predictability, and high volatility of earnings and its components (accruals and cash flows).

Furthermore, we document that low R-square firms tend to have low ROA and the relation with ROA is (almost) exclusively driven by the cash flow component. The accruals remain roughly constant across different R-square firm groups. The smaller contribution of cash flows to ROA over accruals for lower R-square firms is consistent with these firms having lower quality earnings. We also find that the distress measures are all significantly higher for low R-square firms than for high R-square firms.

We find that the AIMR scores are not higher for low R-square firms than for high R-square firms. To the extent that the AIMR score is a valid measure of the reporting environment, this evidence taken together with the previously mentioned evidence is consistent with the view that low R-square is not driven by better disclosure quality, but by high uncertainty about firm-specific fundamentals.

On the basis of our findings that low R-square firms have greater uncertainty about fundamentals and strong accounting-based return anomalies, we conclude that R-square is not just a measure of the *resolved* amount of firm-specific information available in the market. Although low R-square could in principle reflect high and early resolution of firm-specific uncertainty, our evidence instead supports the view that low R-square reflects the fact that the initial and remaining amount of firm-specific uncertainty faced by investors is high, consistent with the *XUV hypothesis*.

In sum, this study contributes to the literature in several ways. First, as an increasing amount of research adopts low R-square as a measure of a high quality of firm-specific information, it is important to evaluate whether this interpretation is accurate. Our evidence raises doubts about this common practice. While there is scattered evidence along these lines in the literature, our paper systematically addresses this issue and opposes this common interpretation. Second, our results indicate that the amount of firm-specific uncertainty about fundamentals is a crucial determinant of the level of R-square. Finally, we document a new source of cross-sectional variation in the strengths of several accounting-based return anomalies. The results therefore have implications for research on market efficiency and the ability of investors to obtain superior portfolio performance.

The results here are derived only within the US stock market, and our conclusion about the meaning of R-square does not necessarily extend to cross-country comparisons. As Bartram, Brown, and Stulz (2009) highlight, across countries there are large variations in uncertainty about country fundamentals, investor protection, financial development, firm diversification, and information environment, all of which determine the cross-country variation in R-square. Their cross-country evidence that idiosyncratic volatility varies inversely with the quality of the information environment is consistent with our findings.

Section I reviews the related literature and motivates our tests. Section II describes the variable measurement, sample and data. Evidence about the relation between R-square and various accounting-based anomalies is presented in Section III. Section IV evaluates the effect of R-square on the explanatory power of future earnings on current returns. The relation between R-square and various factors measuring quality of the information environment is investigated in Section V. Section VI concludes the paper.

I. Background and Hypotheses

A. R-square and Firm-specific Information

Our paper is primarily related to the literature about the interpretation of idiosyncratic stock return volatilities, and by extension the R-square values that correspond to market model regressions, as measuring firm uncertainty. Consistent with the comment of Roll (1988) that low R-squares seem "to imply the existence of either private information or else occasional frenzy unrelated to concrete information," two dramatically different views about what R-squares imply have emerged.

One view posits that lower R-square implies that more firm-specific information is incorporated into stock prices. The first paper to introduce this view is Morck et al. (2000). At the country level, they find that, on average, stock prices in emerging economies have higher synchronicity, i.e. higher R-square values from market model regressions, than those in developed economies, and further that the level of synchronicity is correlated with the degree of private property protection by government. They argue that strong property rights promote informed arbitrage, which facilitates the discovery and utilization of firm-specific information. Consistent with this interpretation, Wurgler (2000) finds that there is a higher elasticity of capital expenditure with respect to value added in countries whose stock returns are less synchronous. In a firm-level study within the US market, Durnev et al. (2003) find that firms with lower R-square values exhibit a higher association between current returns and future earnings, and they regard this as evidence that lower R-square signals more informative stock prices and hence more efficient stock markets.

Since these findings, many studies have adopted this interpretation of R-square. For example, Durnev et al. (2004) employ the same R-square-based measure to examine the relation between stock price informativeness and corporate investment efficiency within the US market. Chan and Hameed (2006) find that greater analyst coverage increases cross-country stock price synchronicity, concluding that analysts primarily produce market-wide information. Piotroski and Roulstone (2004) employ the synchronicity measure to investigate how different types of market participants influence a firm's information environment in terms of firm-specific, industry-level, and market-level information. If, however, low R-square does not proxy for higher price informativeness, many of the conclusions drawn from these results will be called into question.

The second view, originated by Shiller (1981) and West (1988), provides an opposing interpretation. West (1988) provides a theoretical model in which low R-square is associated with less firm-specific information and more noise in returns. More recently, Ashbaugh-Skaife et al. (2006) analyze six of the largest equity markets to examine the effect of R-square on the coefficients of future earnings in regressions that use current returns as the dependent variable. They find results that are contrary to Durnev et al. (2003). Kelly (2007) finds that firms with lower R-squares have a lower quality information environment as characterized by fewer institutional holdings, lower breadth of institutional ownership, lower analyst coverage, lower liquidity, fewer information events, lower flow of informed trades, and higher transaction costs. He concludes that a low R-square is not the result of informed traders impounding firm-specific information in prices.[2] Consistent with Kelly, Evans (2008) finds that low R-square firms are traded more heavily by individual investors, a group that is commonly considered to be less efficient users of public information.

Dasgupta et al. (2009) emphasize that the original interpretation of R-square as a measure of the information environment quality depends on the timing of when R-square is measured. Stock prices are forward-looking and so they are informative about *future* events. Their time series evidence that increased disclosure leads to increased R-square measured in the subsequent period is consistent with the *ER* perspective, in that more

[2] In an effort to reconcile the above two views, Lee and Liu (2006) derive a model that produces a U-shaped relation between price informativeness and idiosyncratic volatility. In their model, extreme low R-square firms and extreme high R-square firms have good information environment, whereas the middle group has poor information environment.

transparency leads to earlier resolution of uncertainty.[3] In time series applications, the *ER* implication is reasonable. However, most past papers using R-square to proxy for the quality of the information environment are cross-sectional studies. Therefore, we focus in this paper on how R-square varies cross-sectionally with the information environment.

B. Accounting-based Anomalies and Information Environment

A large body of empirical research has documented stock returns predictability (for example, Bernard and Thomas (1989), Sloan (1996), Lee, Myers, and Swaminathan (1999), and Hirshleifer et al. (2004)). If risk effects are adequately controlled for in these studies, the results suggest that investors do not process efficiently the information about firm fundamentals that are contained in these predictors. The strength of the anomaly therefore provides a direct measure of the extent to which future information currently contained in the predictors has yet to be incorporated into price. By relating R-square to the strength of well-known anomalies in this paper, we are able to test how R-square relates to the degree of price efficiency more directly.

Hou et al. (2006) use the R-square measure to analyze how investors' private information is related to price momentum. We investigate the relation between R-square and the following four accounting anomalies.

Post Earnings Announcement Drift (PEAD)

Regarded as one of few anomalies that are "above suspicion" and that "have survived robustness checks" (Fama, 1998), PEAD suggests that prices underreact to extreme earnings news, as would occur if some investors failed to react fully to such

[3] There is also a literature on the reasons for the increasing trend in idiosyncratic risk documented in Campbell et al. (2001). See Pastor and Veronesi (2003), Wei and Zhang (2006), Irvine and Pontiff (2009), and Cao et al. (2008)

announcements (Bernard and Thomas, 1990). Good news earnings surprises are followed by positive abnormal returns whereas bad news earnings surprises are followed by negative abnormal returns.

The V/P Anomaly

Lee, Myers and Swaminathan (1999) find that *V/P* is a positive predictor of long-term cross-sectional returns of the Dow 30 stocks. They estimate fundamental value (*V*) using a residual income model and *I/B/E/S* consensus forecasts of earnings. The ratio of *V* over stock price *P*, namely *V/P*, is a measure of the discrepancy between fundamental value and market price, and hence is a straightforward measure of mispricing. Unlike book value, *V* incorporates forward-looking information, namely, analysts' forecasts of future earnings. As a result, *V/P* filters out extraneous information about growth and managerial agency problems better than the book-to-market ratio does (Dong et al., 2006).

The Accrual Anomaly

Sloan (1996) documents that accruals predict negative long-term abnormal stock returns. He suggests that investors fail to fully comprehend the information contained in the decomposition of earnings into cash flows from operations and accruals. Since accruals have less persistence than cash flows for future earnings, investors therefore overreact to the accruals component.

The Net Operating Assets (NOA) Anomaly

Hirshleifer et al. (2004) report that net operating assets (*NOA*) predicts negative long-term abnormal stock returns and future operating profits. They reason that both accounting value added (operating income) and cash value added (free cash flows) are informative about a firm's value. *NOA* represents the cumulative difference over time between the accounting value added and the cash value added,

$$Net\ Operating\ \ Assets_T = \sum_0^T Operating\ \ Income_t - \sum_0^T Free\ Cash\ Flows_t. \tag{1}$$

If investors have limited attention, they may focus on only one of the value added measures, ignoring the other. Higher *NOA* firms have operating income that is less supported by free cash flows, and hence, *NOA* is a parsimonious measure of investors' cumulative over-optimism about fundamental firm value. Consequently, *NOA* is a negative predictor of future returns.

So far, the accounting and finance literatures provide compelling evidence that the anomalous returns findings are hard to reconcile with risk explanations. Trading strategies based on the specified accounting variables yield consistent profits with high Sharpe ratios relative to the market during the period investigated (see, e.g., Bernard and Thomas, 1990; Sloan, 1996; Hirshleifer et al. 2004) and the profits are robust to an extensive set of asset pricing controls (Ali et al., 2003; Hirshleifer et al., 2004). The evidence that a substantial portion of the abnormal returns obtains around future earnings announcement dates requires an exceptionally high risk premium and a particular varying pattern over time for the risk explanation to be justified. Hirshleifer et al. (2006) demonstrate that it is the accruals and *NOA* characteristics rather than the factor loadings that predict returns in both time-series and cross-sectional tests, favoring a behavioral explanation for the accruals and *NOA* anomalies.

The common theme thus far is that investors are unable to fully digest the information available in financial variables. Hirshleifer and Teoh (2003) model investors' limited attention as a general explanation for accounting-based anomalies. A testable prediction from the model is that the relevant trading strategies should yield higher profits among firms characterized by a lower quality information environment or complex fundamentals since such stocks are more costly to analyze. There is extensive empirical evidence consistent with this prediction. For example, PEAD is particularly strong among small firms (Bernard and Thomas, 1990), the accruals effect is weaker for firms with more transient institutional holdings (Collins, Gong, and Hribar 2003), and Zhang (2006) finds that price momentum works better for samples in which uncertainty is greater.

C. Hypotheses

In this study we test between these alternative hypotheses in a cross-sectional setting for the US market:

The Early Resolution (ER) Hypothesis:

Low R-square reflects a good information environment because there is more historical resolution of firm-specific uncertainty, resulting in low remaining uncertainty.

The Cross-Sectional Uncertainty Variation (XUV) Hypothesis:

Low R-square reflects a poor information environment because there is high remaining firm-specific uncertainty.

To test between the alternative hypotheses, we use the strength of anomalies to proxy for measures of the quality of the firm information environment. We expect that firms with a poor information environment (high uncertainty) will have stronger anomalies, whereas firms with high quality information environment will have weaker anomalies. A finding that low R-square is associated with weaker anomalies would be supportive of the *ER Hypothesis*, and consistent with Durnev et al.'s (2003) interpretation for R-square. On the other hand, a finding of a negative relation between R-square and anomaly strength is supportive of the *XUV Hypothesis*.

II. Variable Measurement and Sample

A. R-square

The construction of our R-square measure follows Morck et al. (2000) and Durnev et al. (2003). In particular, we perform the following regression each year for each firm *j*:

$$r_{j,w,t} = \alpha_{j,t} + \beta_{j,t} r_{m,w,t} + \gamma_{j,t} r_{i,w,t} + \varepsilon_{j,w,t} , \qquad (2)$$

where $r_{j,w,t}$ is firm *j*'s total returns in week *w* of fiscal year *t*, $r_{m,w,t}$ is the market return in week *w* of fiscal year *t*, $r_{i,w,t}$ is the return for industry *i* based on the two-digit SIC code in week *w* of fiscal year *t*. Both the market return and industry return in (2) are value-weighted averages excluding the firm in question. That is, when firm *j*'s weekly return $r_{j,w,t}$ is the dependent variable in (1), the industry return is defined as

$$r_{i,w,t} = \frac{\sum_{k \in i} W_{k,w,t} r_{k,w,t} - W_{j,w,t} r_{j,w,t}}{J_{i,w} - 1} , \qquad (3)$$

where $W_{k,w,t}$ is the value weight of firm *k* in industry *i* in week *w* of year *t*, and $J_{i,w}$ is the number of firms in industry *i* that firm *j* belongs to in week *w*. The market return $r_{m,w,t}$ is defined similarly.

Following the literature, we define the R-square-based measure that we use in later analyses, *SYNCH*, as

$$SYNCH_{j,t} = \log\left(\frac{R^2_{adj\ \ j,t}}{1 - R^2_{adj\ \ j,t}}\right) , \qquad (4)$$

where $R^2_{adj\ j,t}$ is the adjusted R-square value from regression (2) for firm *j* in year *t*. Each year we require each firm to have at least 40 weeks of returns data to be included in the regression.

B. Measurement of Accounting Predictors of Stock Returns

***Standardized Unexpected Earnings* (*SUE*)**

Following Bernard and Thomas (1990), we define the standardized unexpected earnings, *SUE*, as seasonal differences in quarterly earnings, scaled by its historical standard deviation. A minimum of eight up to a maximum of twenty-four quarters of earnings are required to estimate the standard deviation. As in Bernard and Thomas (1990), the magnitude of *SUE* is winsorized at five.

V/P

We use the *V/P* as calculated in Hirshleifer et al. (2006). The variable *V* is a measure of a stock's fundamental value and is derived from the Edwards-Bell-Ohlson discounted residual-income valuation model. Specifically, V is measured as:

$$\hat{V}_t = B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)} B_t + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2} B_{t+1} + \frac{(FROE_{t+3} - r_e)}{(1+r_e)^2 r_e} B_{t+2}, \qquad (5)$$

where B_t is the book value at time *t*, $FROE_{t+i}$ is the forecasted return on book equity for period $t+i$, measured as $FROE_{t+i} = FEPS_{t+i} /((B_{t+i-1} + B_{t+i-2})/2)$, *FEPS* is the *I/B/E/S* consensus earnings forecasts used to estimate expected future *ROEs,* and r_e is the firm's cost of capital estimated using the capital asset pricing model, CAPM. Price (*P)* is the stock price at the end of June in year *t - 1*. For details see Hirshleifer et al. (2006).

Accruals

We calculate accruals using the following indirect balance sheet approach as in (6)

(Sloan, 1996) for all fiscal years in our sample. Specifically, we calculate accruals as follows (firm identifier subscripts suppressed):

$$Accruals_t = (\Delta Current\ Assets_t - \Delta Cash\ and\ Short\ Term\ Investment_t)$$

$$- (\Delta Current\ Liabilities_t - \Delta Short\text{-}Term\ Debt_t - \Delta Tax\ Payable_t) - Depreciation_t\,. \quad (6)$$

Net Operating Assets (NOA)

Net operating assets are calculated as the difference between operating assets and operating liabilities (Hirshleifer et al., 2004), where (firm identifier subscripts suppressed)

$$Operating\ Assets_t = Total\ Assets_t\text{-}Cash\ and\ Short\ Term\ Investment_t,$$

$$Operating\ Liabilities_t = Total\ Assets_t\text{-}Short\text{-}Term\ Debt_t\ \text{-}Long\ Term\ Debt_t$$

$$\text{-}Minority\ Interest_t\text{-}Preferred\ Stock_t\text{-}Common\ Equity_t\,. \quad (7)$$

Both accruals and net operating assets are scaled by fiscal-year-beginning total assets (Compustat #6) to obtain the scaled variables, *SACCRUAL* and *SNOA*, respectively.[4] To avoid undue effects caused by extremely small denominators, we delete observations with beginning total assets smaller than one million US dollars. If short-term debt or taxes payable in (6) have missing values, we set their values to zero to avoid loss of observations.

C. Abnormal Returns

In calculating the abnormal returns associated with various financial anomalies, except the post-earnings announcement drift, we adopt the characteristics approach proposed by Daniel and Titman (1997) to simultaneously control for the three asset

[4] The main results are not affected by the choice of ending total assets or average total assets as deflators for accruals and net operating assets.

pricing factors, size, book-to-market (*BTM*), and momentum to better isolate the anomalous effect investigated. The empirical evidence provided by Daniel et al. (1997) suggests that these characteristics provide *ex ante* forecasts of the cross-sectional patterns for future returns. Following the literature, we use size-adjusted returns to examine the post-earnings-announcement drift.

Specifically, for each month, we form the size-BTM-momentum quintile benchmark portfolios (in total, 5*5*5=125 portfolios) based on NYSE stocks cutoff points. To calculate monthly characteristics-adjusted returns (hereafter "abnormal returns"), we then subtract the equal-weighted returns of the size-BTM-momentum benchmark portfolio to which the firm belongs from the firm's raw buy-and-hold returns for each month. To ensure that the information available in annual financial statements is incorporated into stock prices, the financial data are matched with returns starting from the fifth month to the sixteenth month after the fiscal-year-end.[5]

D. Earnings Attributes

In examining the relation between R-square and firms' fundamentals, among various measures we consider several measures of earnings attributes, including accruals quality, persistence, predictability, and smoothness, as defined below. Our definitions mainly follow Francis et al. (2004).

Our measure of accruals quality is based on the residual standard deviation in the Dechow and Dichev's (2002) regression model that relates current accruals to lagged,

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[5] In addition, whenever we discuss the relation between the synchronicity measure, *SYNCH*, and abnormal returns (see Section III), we make sure that the returns information contained in *SYNCH* does not overlap with that of the abnormal returns concerned. Actually there is at least a four-month lag in the returns information contained in *SYNCH* compared to the information contained in abnormal returns.

current, and future cash flows from operations:

$$\frac{TCA_{i,t}}{Assets_{i,t}} = \alpha_{0,i} + \alpha_{1,i}\frac{CFO_{i,t-1}}{Assets_{i,t}} + \alpha_{2,i}\frac{CFO_{i,t}}{Assets_{i,t}} + \alpha_{3,i}\frac{CFO_{i,t+1}}{Assets_{i,t}} + \varepsilon_{i,t}\ , \qquad (8)$$

The accruals quality measure, $EQ\_DD_{i,t}$, is calculated as $\sigma(\hat{\varepsilon}_{i,t})$, that is, the standard deviation of firm *i*'s estimated residuals. Larger values of $EQ\_DD_{i,t}$ indicate lower accruals quality.

We estimate earnings persistence from an earnings autoregressive model of order one:

$$EPS_{i,t} = \beta_{0,i} + \beta_{1,i}EPS_{i,t-1} + \eta_{i,t}\ , \qquad (9)$$

where $EPS_{i,t}$ is earnings per share for firm *i* in year *t*, calculated as firm *i*'s net income before extraordinary items in year *t* divided by the number of outstanding shares at the end of fiscal year *t*. Earnings persistence is measured as the slope coefficient estimate, $\hat{\beta}_{1,i}$. In order to align the ordering of this variable with other earnings attributes, we define the variable *PERSIST* = - $\hat{\beta}_{1,i}$, so that larger values of *PERSIST* correspond to less-persistent earnings.

Earnings predictability is measured as the square root of the error variance from regression (9), $PREDICT = \sigma(\hat{\eta}_{i,t})$. Larger values of *PREDICT* indicate less predictable earnings.

We define earnings smoothness as the ratio of firm *i*'s standard deviation of net income before extraordinary items to firm *i*'s standard deviation of cash flows from operations. That is, $SMOOTH_{i,t} = \sigma(NIBE_{i,t}) / \sigma(CFO_{i,t})$. Larger values of *SMOOTH* imply less earnings smoothness.

For the earnings quality measures obtained from models (8) and (9) above, consistent with the literature, we estimate the model regressions using rolling windows of up to fifteen years with a minimum of five years data for each firm. We also calculate the standard deviation of earnings (*STD_SEARN*), standard deviation of accruals (*STD_SACCRUAL*), and standard deviation of cash flows (*STD_SCF*) over 15-year rolling windows, with a minimum of five years of data.

E. Financial Distress

We consider two proxies to measure financial distress. The first is Altman's (1968) Z-score (firm-year subscripts suppressed),

$$\begin{aligned} Z-score &= 1.2*(Working\ Capital/Assets)+1.4*(Retained\ Earnings/Assets) \\ &+3.3*(EBIT/Assets)+0.6*(MV/Liabilities)+(Sales/Assets) \end{aligned} \quad (10)$$

where *Assets* is the total assets of the firm-year concerned, *EBIT* is earnings before interest and taxes, *MV* is the market value of equity, and *Liabilities* is the book value of total liabilities. Larger values of *Z-score* correspond to lower probabilities of bankruptcy. To be consistent with the other bankruptcy risk measure, we define *ZSCOREN* = (-1)**Z-score* such that larger values of *ZSCOREN* imply higher probabilities of bankruptcy.

The second proxy is the market-information-based bankruptcy risk measure developed by Hillegeist et al. (2004) on the basis of the Black-Scholes-Merton option pricing model. Hillegeist et al. show that this measure is more informative about a firm's distance from bankruptcy than other prior measures. The formula for deriving this bankruptcy probability measure, *BSMPROB*, is

$$BSMPROB = N\left(-\frac{\ln(V_A / X) + (\mu - \delta - (\sigma_A^2 / 2))T}{\sigma_A \sqrt{T}}\right), \tag{11}$$

where *N(.)* is the standard cumulative normal distribution, V_A is the current market value of assets, X is the face value of liabilities, μ is the continuously compounded expected return on assets, δ is the continuous dividend rate, σ_A is the volatility of assets, and T is the length of the period before the liability expires, which we set to one in our calculation.[6]

F. Sample and Data Description

The sample covers NYSE, AMEX, and NASDAQ firms with available data from the intersection of CRSP and COMPUSTAT data sets during the period from July 1964 to December 2002. All firm-year observations are required to have sufficient financial data to compute the variables needed in the respective tests. Specifically, for *V/P*, our sample period begins in 1980, when *I/B/E/S* analyst forecast data is available. Thus, the final sample size for each test varies across analyses due to different data restrictions.

Table I provides descriptive statistics for the main variables used in later analyses. The dramatic difference between the mean and median of market value (*MV*) reveals that our sample contains some very large firms. For all variables, there is reasonable variation in the values of the variables, and are generally consistent with the range of values in prior literature. On average, *SYNCH* is -1.15, reflecting that mean R-square of firms is small and generally below 50%, again consistent with prior literature.

The Spearman correlation coefficients between the main control variables and the

[6] Using the weighted-average maturity period for long-term debt does not qualitatively change our results.

four anomaly variables are presented in Table II. The correlation of *SYNCH* with firm size (MV) is large (0.32) and is somewhat smaller with book-to-market (BTM, -0.06), both correlations are statistically significant. This indicates a need to control for the size variable in our tests. We also find that the correlations of *SYNCH* with the anomaly variables, *SACCRUAL, SNOA, SUE,* and *V/P*, while statistically significant, are small in magnitude. Therefore, there should be sufficient variation of *SYNCH* and anomaly variables in the subsequent double-sorting analyses.

III. R-square and Anomalies

Under the *ER Hypothesis*, low R-square is associated with more firm-specific information about future cash flows being impounded into stock prices. Investors are more likely to understand the fundamentals and related accounting information of low R-square firms than high R-square firms. Therefore, we should observe a positive association between *SYNCH* and the strength of the anomalies. In contrast, the *XUV Hypothesis* offers the opposite prediction. Under this hypothesis, low R-square firms have greater firm-specific uncertainty yet to be solved compared to high R-square firms. Investors of low R-square firms have greater difficulty in understanding information about future fundamentals that are contained in current accounting measures than high R-square firms. Thus, *SYNCH* is negatively related to the strength of anomalies.

We adopt a double-sorting technique for each anomaly. For *V/P, Accruals* and *NOA* anomalies, at the beginning of each month between July 1964 (July 1980 for *V/P* due to the requirement of I/B/E/S data) and December 2002, firms are first ranked by *SYNCH* into four groups. Then, firms are ranked by each of the accounting predictors (*V/P* in descending order, *Accruals* and *NOA* in ascending order) into four portfolios. A hedging strategy that goes long in the lowest predictor quartile and shorts the highest predictor quartile is implemented for each *SYNCH* portfolio.[7] The time-series average means of the monthly hedge returns along with the associated t-statistics are reported in Table III. For the PEAD anomaly, we double sort first by *SYNCH*, then by *SUE* every quarter for the fiscal period from 1974 to 2002. We report the hedge profits for the period from one day after the earnings announcement to two days prior to the next earnings announcement date or for the three-day period surrounding the next earnings announcement date.

A. R-square and Post-earnings-announcement Drift

The last column of Panel A-1 in Table III exhibits the trading profit for the PEAD anomaly for each *SYNCH* portfolio for the period from one day after the earnings announcement to two days prior to the next earnings announcement date. Buying the highest *SUE* portfolio and selling the lowest *SUE* portfolio within the lowest *SYNCH* portfolio generates a 6.21% size-adjusted return for the period. As the investment strategy is performed in higher *SYNCH* quartiles, this return drops monotonically from 4.56% to 3.84%, and then to 2.44% in the highest *SYNCH* quartile. The difference of the *SUE* hedge returns between the lowest and the highest *SYNCH* quartile is a statistically significant 3.77%. Therefore, low R-square firms exhibit stronger PEAD.

Prior research shows that the drift returns are disproportionately concentrated around future earnings announcement periods, especially the subsequent quarter. The evidence is consistent with market mispricing and its subsequent correction when earnings information is released (Bernard and Thomas, 1990). We show in Panel A-2 of Table III

[7] The empirical results are robust to the choice of equal-weighted or value-weighted portfolios.

the three-day cumulative abnormal returns surrounding the subsequent earnings announcement date. The three-day abnormal returns still show a monotonically decreasing trend as we move from the lowest to the highest *SYNCH* quartile. The return difference between the two extreme *SYNCH* quartiles is 0.68%, which is highly statistically significant. Our evidence demonstrates that the correction of mispricing when subsequent quarter earnings is released is much stronger for low *SYNCH* firms than for high *SYNCH* firms. Therefore, low R-square firms have later resolution of uncertainty than high R-square firms.

B. R-square and V/P Anomaly

Panel B of Table III presents investment returns from an investment strategy on the basis of double sorting first on *SYNCH* and then on *V/P* (in reverse order). Again, moving from the lowest to the highest *SYNCH* quartile, we find a monotonic decrease of returns from an investment strategy buying the lowest *V/P* quartile portfolio (most undervalued) and selling the highest *V/P* quartile portfolio (most overvalued). The average monthly abnormal returns are 1.84%, 1.80%, 1.62%, and 1.33%, respectively, from the lowest to the highest *SYNCH* quartiles during the 12-month period after the formation of the portfolios. The difference between the lowest and highest *SYNCH* quartiles is 0.51% and is statistically significant. Low R-square firms have stronger *V/P* anomalies.

C. R-square and the Accruals Anomaly

In the last column of Panel C of Table III, we observe a monotonically decreasing relation between the magnitude of *SYNCH* and the monthly abnormal returns from a zero-investment strategy based on the *Accruals* (*SACCRUAL*) sorting (long in the lowest accruals quartile and short in the highest Accruals quartile). Specifically, within the lowest *SYNCH* quartile portfolio, the Accruals strategy generates an abnormal return of 0.68% per month, more than three times that of the highest *SYNCH* quartile (0.20% per month). The difference of the Accruals hedge profits between the lowest and highest *SYNCH* quartiles is 0.48%, significant at lower than 1% level. Low R-square firms have stronger accrual anomalies.

D. R-square and the Net Operating Assets (NOA) Anomaly

The relation between R-square and the *NOA* anomaly is presented in Panel D of Table III. Our findings are similar to those for the Accruals anomaly. We find a monotonic negative relation between *SYNCH* and abnormal returns based on the *NOA* strategy. In the lowest *SYNCH* quartile portfolio, buying the lowest-quartile *NOA* and selling the highest-quartile *NOA* produces an average monthly buy-and-hold return of 1.16% over the next 12-month period, which is equal to a 13.92% annualized return. Moving from the second to the fourth *SYNCH* quartile, the same zero-investment strategy generates monotonically decreasing average monthly returns of 0.93%, 0.86%, and 0.61%, respectively. The difference in hedge profits across the lowest and highest *SYNCH* quartiles is 0.55% and is statistically significant. Low R-square firms have stronger *NOA* anomalies.

In summary, the declining trading profit patterns across the *SYNCH* quartiles for all four anomalies contradict the *ER Hypothesis*. Low R-square firms have stronger anomalies. Apparently, any early resolution for low R-square firms from current accounting variables does not resolve as much uncertainty to allow investors to better evaluate future firm fundamentals as compared with firms with high R-square. Overall, the evidence suggests that stock prices are less able to track fundamentals for low R-square firms, which impedes the efficient functioning of the capital market among these firms.

IV. R-square and Price Informativeness About Future Earnings

Substantiating Morck et al.'s (2000) argument that low R-square is a measure of greater amount of firm-specific information impounded in the stock price, Durnev et al. (2003) offer direct evidence by studying the association between R-square and price informativeness. We revisit this test using an alternative test method to theirs but identical price informativeness proxies.

The first proxy, the future earnings response coefficients (*FERC*), is estimated by the sum of the coefficients on future earnings changes when current annual returns are regressed on current-period unexpected earnings and future earnings changes, with future stock returns included to control for noise in measuring market expectation of future earnings:

$$r_t = a + b_0 \Delta E_t + \sum_{\tau} b_{\tau} \Delta E_{t+\tau} + \sum_{\kappa} c_{\kappa} r_{t+\kappa} + \mu_t \ , \qquad (12)$$

where r_t is the current annual stock returns, ΔE_t is current-period change in earnings per share, and $\Delta E_{t+\tau}$ is the earnings per share change τ periods ahead, both scaled by the price at the beginning of the current year. $r_{t+\kappa}$'s are future period stock returns, and

$$FERC \equiv \sum_{\tau} b_{\tau} \ . \qquad (13)$$

The second price informativeness proxy (*FREL*) measures the incremental explanatory power of future earnings in regression (12), is defined as

$$FREL \equiv R^2_{r_t = a + b_0 \Delta E_t + \sum_{\tau} b_{\tau} \Delta E_{t+\tau} + \sum_{\kappa} c_{\kappa} r_{t+\kappa} + \mu_t} - R^2_{r_t = a + b_0 \Delta E_t + \mu_t} \ , \qquad (14)$$

where R^2 is the adjusted r-square from the OLS regression of the model denoted in the subscript.

Durnev et al. find that firms with lower *SYNCH* exhibit higher *FERC* and higher *FREL*, indicating that there is more information about future earnings in current stock returns. They conclude that lower R-square "signals more information-laden stock prices and, therefore, more efficient stock markets." For completeness, we also compute *CERC* as the contemporaneous period earnings response coefficient b_0 in regression (12), and *CREL* as the r-square statistic in the regression of returns on the contemporaneous period change in earnings.

Durnev at al. use an industry-matching approach to control for industry-related factors in R-square, and select only two pairs of extreme R-square firms in each industry to study. Consistent with Ashbaugh-Skaife et al. (2006), we choose to use all firms in the industry and a regression approach with controls. As a comparison, the sample size in Durnev et al. (2003) is 500 firms, whereas our method permits a sample of 44,000 observations.

We employ the rolling-window regression method to obtain firm-year specific observations of *FERC* and *FREL* as well as *CERC* and *CREL*. Specifically, in regression (12), for a given firm, to obtain the price informativeness measures for year t, we use observations from year *t-14* to year *t*.[8] To maximize sample size and estimation degrees of freedom, we only control for one period of future returns. That is, we set $\tau = 3$ and $\kappa = 1$.[9]

We present the descriptive relation between R-square and the price informativeness

[8] The results are essentially the same if we use ten-year or eight-year rolling windows.
[9] Setting *k*=3 does not qualitatively change our results.

measures in Table IV. Corresponding to the 15-year time window for the price informativeness measures, we average *SYNCH* also over the past fifteen years to obtain *MSYNCH* for each firm-year. All firm-years are divided into ten portfolios based on *MSYNCH*.

In Table IV, the mean and median of *FERC* and *FREL* increase almost monotonically with *MYSNCH* up to decile 8 and then stay high for the two top most deciles. The range is from 2.14 to 5.34 for mean *FERC* and 2.8% to 6.9% for mean *FREL*. The median values are of similar magnitudes. Hence, higher R-square is associated with price impounding a greater amount of future earnings news. This is inconsistent with Durnev et al. (2003) and consistent with Ashbaugh-Skaife et al. (2006).

For completeness, we also describe the association of R-square with contemporaneous period earnings response coefficient as measured by *CERC* and *CREL*. These measures generally decrease with *MSYNCH*. When combined with the results for *FERC* and *FREL* and keeping in mind that stock prices are forward-looking, the evidence suggests that firms with low R-square have late resolution of uncertainty. For low R-square firms, less information was anticipated prior to each earnings announcement and so that at the next earnings announcement date, a greater amount of historical uncertainty is resolved. Thus, the evidence is consistent with the *XUV* hypothesis and is inconsistent with the *ER* hypothesis. Before we present the regression results that control for other factors that may affect price informativeness (see Panel C Table V), we first document how R-square is associated with earnings-based measures of the quality of information environment.

V. R-square and Earnings Properties

The quality of the information environment comes from both uncertainties about fundamentals and the quality of financial reporting. We examine the relation between R-square and the quality of the information environment by focusing on the firm's earnings attributes. We concentrate on earnings because they are the primary source of information about firm fundamentals, and are widely and readily available.

Table V Panel A reports the relation between one-year lag *SYNCH* and the level of earnings as a proxy for firm performance. *SEARN* is earnings before extraordinary items deflated by beginning-of-year total assets; so it is equivalent to the return on assets. As lagged *SYNCH* increases across deciles, mean *SEARN* increases almost monotonically from 0.06 to 0.14, implying that firms with higher R-square have better fundamental performance. Our cross-sectional results complement Wei and Zhang's (2006) time-series finding that deteriorating earnings quality is the source for the trend of increasing idiosyncratic volatility documented in previous literature.

Considering the earnings components, we find that the improving earnings performance across R-square deciles come from the cash flows from operations (SCF) component. Mean *SCF* increases from 0.09 to 0.17 across lagged *SYNCH* deciles. The accruals component varies little across the *SYNCH* deciles. All patterns are similar for median measures. Earnings of high R-square firms therefore are supported more by cash flows from operations than from accounting adjustments, and are therefore of higher quality.

Turning next to measures of uncertainty about performance in the lower rows of Panel A in Table V, we measure variability over rolling periods of the past 15 years for each firm-year. For consistency, we examine the variability of performance with *MSYNCH*. We find that the variability of earnings and that of both its components decline monotonically across the deciles of *MSYNCH*.[10] The differences in the standard deviations of scaled earnings, accruals, and cash flows from operations between the lowest and highest *MSYNCH* deciles are all statistically significantly positive, suggesting that higher R-square firms have lower uncertainty about fundamentals.

Next, we study how R-square is associated with various earnings properties, including accruals quality (*EQ_DD*), earnings persistence (*PERSIST*), earnings predictability (*PREDICT*), and earnings smoothness (*SMOOTH*) as defined in Section II. The empirical findings from univariate analyses are presented in Panel B of Table V. Note that all four variables are measured such that larger values of the measured variables imply lower accrual quality, and lower earnings persistence, predictability and smoothness to be consistent with past literature. We find that each of these variables, *EQ_DD*, *PERSIST*, *PREDICT*, and *SMOOTH*, decrease nearly monotonically as *SYNCH* increases. The differences in these variables between the two extreme deciles are all statistically significantly positive. Low R-square firms therefore have lower accruals quality, and earnings that are less persistent, less predictable, and less smooth. These findings again support the view that low R-square firms are associated with lower earnings quality.

Since univariate analyses may be biased by omitted correlated variables, we also perform multivariate regression analyses by including all the earnings-related variables and the previous price informativeness measures using earnings response coefficients as test variables, and firm size as control. The results are reported in Panel C of Table V. The coefficients on *EQ_DD* and *SMOOTH* are no longer statistically significant, though they maintain the same sign, but the estimated coefficients on the other variables are

[10] Similar results are obtained using *SYNCH* as for *MSYNCH*.

consistent with the univariate results. Jointly, the evidence suggests that the high R-square firm has lower fundamental uncertainty and/or better reporting quality, and its stock price anticipates a greater amount of future news earlier than low R-square firms. In sum, the evidence is consistent with the *XUV* hypothesis.

Lastly, we investigate the relation of R-square to three additional measures that are associated with firm uncertainty about fundamentals, namely, the occurrence of losses and two financial distress variables (the transformed Altman Z-score *ZSCOREN* and a bankruptcy probability measure *BSMPROB* that is calculated using the Black-Scholes-Merton framework). Univariate results are reported in Panel A of Table VI.

As *SYNCH* increases, the percentage of firms that experience a loss decreases. There are 24% loss firms in the lowest *SYNCH* decile as compared with only 5% in the highest *SYNCH* decile. Similarly, firms with low R-square also face greater bankruptcy risk, measured by either of the two proxies. The lowest *SYNCH* decile has a mean bankruptcy probability of as high as 6.30%, while the highest *SYNCH* decile experiences a mean bankruptcy probability of only 0.6%. The differences between the two extreme groups are statistically significant for all three measures. Multivariate regression results in Panel B of Table VI corroborate these findings. All the *t*-statistics for the financial distress variables, *LOSS*, *ZCOREN*, and *BSMPROB*, are highly significant in the same direction as in the univariate results. The evidence is therefore consistent with the *XUV* hypothesis.

In Table VII, we directly investigate the relation between R-square and investors' perception of corporate transparency, which is traditionally measured as AIMR scores in the accounting literature.[11] Univariate results show that reporting transparency score

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[11] Between 1980 and 1995, the Association of Investment Management Research conducted an annual

decreases with R-square but after controlling for firm size, the coefficient on AIMR is no longer significant. Therefore, the difference in R-square is driven more by differences in uncertainty about fundamentals than by differences in disclosure quality.

VI. Summary and Conclusion

This paper is motivated by Durnev et al.'s (2003) proposition that R-square is a measure of the degree to which firm-specific information is accurately impounded in stock prices, and so low R-square firms have more efficient stock valuation. We argue that if this interpretation is valid, we should observe weaker financial anomalies among firms with lower R-square. This provides a direct test of the relation between R-square and market efficiency. Tests on four well-documented financial anomalies—post-earnings announcement drift, *V/P*, accruals, and net operating assets anomalies—all yield the opposite effect that high R-square firms have more efficient stock prices.

We further directly examine the association between R-square and price informativeness, using the incremental explanatory power of future earnings on current returns as a proxy for informativeness. Using a different test method that allows for a much larger sample, we find evidence inconsistent with Durnev et al. (2003). Our analyses on the association between R-square and earnings properties and distress measures reveal that R-square is more a positive rather than an inverse measure of firm-specific quality of the information environment. In sum, our evidence indicates that R-square differences measure cross-sectional differences in uncertainty about the information environment, primarily from uncertainty about fundamentals.

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survey among financial analysts to rate companies' disclosure practices both in quality and quantity of disclosure. The AIMR scores are within-industry ranks of the analysts' scores.

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Table I
Descriptive Statistics

SYNCH $= \log(\frac{R^2_{adj}}{1-R^2_{adj}})$, where R^2_{adj} is adjusted R-square statistics from within-firm-fiscal-year regressions of the market model using weekly stock returns data that also include industry returns. *BETA*: beta coefficients from the market model regression. *MV*: market value, defined as stock price per share*number of shares outstanding at the end of each fiscal year. *BTM*: book to market values of the common equity. *SEARN*: earnings before extraordinary items deflated by total assets at the beginning of the year. *SACCRUAL*: total accruals deflated by total assets at the beginning of the year. *EQ_DD*: the measure of accruals quality following Dechow and Dichev (2002). *STD_SEARN*: standard deviation of *SEARN* of each firm calculated over fifteen-year rolling windows. *STD_SACCRUAL*: standard deviation of *SACCRUAL* of each firm calculated over fifteen-year rolling windows. *STD_SCF*: standard deviation of SCF of each firm calculated over fifteen-year rolling windows, in which *SCF* is the difference between *SEARN* and *SACCRUAL*. *PERSIST*: earnings persistence, measured as (-1* $\hat{\beta}_{1,i}$), where $\hat{\beta}_{1,i}$ is estimated from regression (9): $EPS_{i,t} = \beta_{0,i} + \beta_{1,i} EPS_{i,t-1} + \eta_{i,t}$ over fifteen-year rolling windows. *PREDICT*: earnings predictability, defined as $\sigma(\hat{\eta}_{i,t})$, where $\hat{\eta}_{i,t}$ is the estimated residual from regression (9) over fifteen-year rolling windows. *SMOOTH*: the ratio of a firm's standard deviation of net income before extraordinary items to its standard deviation of cash flows from operations, namely, $SMOOTH_{i,t} = \sigma(NIBE_{i,t}) / \sigma(CFO_{i,t})$, calculated over fifteen-year rolling windows. *CREL*: value relevance of current earnings, measured as the explanatory power of current-period earnings changes on current-period stock returns, namely, the R-square statistic from the regression: $r_{i,t} = a_i + b_i \Delta E_{i,t} + \mu_{i,t}$. *FREL*: value relevance of future earnings, measured as the incremental explanatory power of future-period earnings changes on current period stock returns, namely, $FREL \equiv R^2_{r_t = a + b_0 \Delta E_t + \sum_\tau b_\tau \Delta E_{t+\tau} + \sum_\kappa c_\kappa r_{t+\kappa} + \mu_t} - R^2_{r_t = a + b_0 \Delta E_t + \mu_t}$. *SNOA*: net operating assets, defined as (Total Assets-Cash and Short Term Investment)-(Total Assets-Short Term Debt-Long Term Debt-Minority Interest-Preferred Stock-Common Equity), deflated by total assets at the beginning of the year. *SUE*: unexpected earnings derived from the first-order autoregressive model deflated by the standard deviation of the forecast errors in the estimation period; a minimum of eight quarters up to a maximum of twenty-four quarters of earnings are required for the estimation. *V/P*: the ratio of a stock's fundamental value derived from the Edwards-Bell-Ohlson (EBO) discounted residual-income valuation model to the stock price at the end of June of the previous year. *LOSS*: an indicator variable that takes the value of one if the firm concerned incurs a loss in the year and zero otherwise. *ZSCOREN*: transformed from Altman's Z-score by (-1)*Z-score and Z-score=1.2*(working capital/assets)+1.4*(retained earnings/assets)+3.3*(EBIT/assets)+0.6*(MV/liabilities)+sales/assets. *BSMPROB*: a market-information-based bankruptcy risk measure, derived following Hillegeist et al. (2004).

	n	mean	median	std	p1	p99
Panel A: Market attributes						
SYNCH	95085	-1.15	-1.37	2.06	-5.86	3.88
BETA	78864	1.15	1.13	0.62	-0.25	2.76
MV	100743	1276	82	7925	1	21531
BTM	100743	5.57	0.65	623.19	-1.00	4.10
Panel B: Earnings attributes						
SEARN	100743	0.07	0.09	0.25	-0.78	0.47
STD_SEARN	44715	0.02	0.001	0.28	0.000	0.20
STD_SCF	44715	0.02	0.004	0.28	0.000	0.20
STD_SACCRUAL	44715	0.01	0.004	0.09	0.001	0.11
EQ_DD	44715	0.00	0.00	0.01	0.00	0.03
PERSIST	44715	-0.47	-0.47	0.43	-1.49	0.46
PREDICT	44715	0.05	0.03	0.09	0.00	0.36
SMOOTH	44715	0.62	0.37	1.25	0.01	3.53
CREL	44715	0.05	0.00	0.20	-0.29	0.66
FREL	44313	0.04	0.01	0.35	-0.90	0.93
Panel C: Return predictors						
SACCRUAL	100743	-0.03	-0.04	0.17	-0.38	0.38
SNOA	100743	0.71	0.71	0.51	-0.07	1.84
SUE	49556	0.32	0.18	1.51	-4.00	5.00
V/P	47894	5.21	0.69	945.17	0.02	4.02
Panel D: Distress proxies						
LOSS	100743	0.20	0.00	0.40	0.00	1.00
ZSCOREN	96567	-2.76	-2.95	4.14	-11.32	10.64
BSMPROB	86664	0.04	0.00	0.12	0.00	0.65

Table II
Spearman Correlation Coefficients

$SYNCH = \log(\frac{R^2_{adj}}{1 - R^2_{adj}})$, where R^2_{adj} is adjusted R-square statistics from within-firm-fiscal-year regressions of the market model using weekly stock returns data that also includes industry returns. *MV*: market value, defined as stock price per share*number of shares outstanding at the end of each fiscal year. *BTM*: book to market values of the common equity. *SEARN*: earnings before extraordinary items deflated by total assets at the beginning of the year. *SACCRUAL*: total accruals deflated by total assets at the beginning of the year. *SNOA*: net operating assets, defined as (Total Assets - Cash and Short Term Investment)-(Total Assets-Short Term Debt-Long Term Debt-Minority Interest-Preferred Stock-Common Equity), deflated by total assets at the beginning of the year. *SUE*: unexpected earnings derived from the first-order autoregressive model deflated by the standard deviation of the forecast errors in the estimation period; a minimum of eight up to a maximum of twenty-four quarters of earnings are required for the estimation. *V/P*: the ratio of a stock's fundamental value derived from the Edwards-Bell-Ohlson (EBO) discounted residual-income valuation model to the stock price at the end of June of the previous year. P-values are shown below the correlation coefficients.

	SYNCH	MV	BTM	EQ_DD	SACCRUAL	SNOA	SUE	V/P
SYNCH	1.00	0.32	-0.06	-0.17	0.03	0.06	0.01	0.04
		<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.028*	*<.0001*
MV		1.00	-0.37	-0.42	0.01	0.06	0.02	-0.05
			<.0001	*<.0001*	*0.004*	*<.0001*	*0.001*	*<.0001*
BTM			1.00	-0.08	0.00	0.11	-0.11	0.29
				<.0001	*0.928*	*<.0001*	*<.0001*	*<.0001*
EQ_DD				1.00	-0.06	-0.21	0.04	-0.17
					<.0001	*<.0001*	*<.0001*	*<.0001*
SACCRUAL					1.00	0.33	0.03	0.01
						<.0001	*<.0001*	*0.086*
SNOA						1.00	-0.01	0.08
							0.045	*<.0001*
SUE							1.00	-0.12
								<.0001
V/P								1.00

Table III

Two-way Sorting

SYNCH , *SUE*, *V/P, SACCRUAL and SNOA* are defined as in Table I. For PEAD, the cumulative size-adjusted returns from one trading day after the current earnings announcement date to two trading days before the next earnings announcement date are reported in Panel A-1. The cumulative size-adjusted returns for the three-trading-day period surrounding the next earnings announcement date, namely (-1, +1), are reported in Panel A-2. For V/P, Accruals, and NOA anomalies, average monthly hedge returns (adjusted for size, book to market, and momentum-effect factors) across up to twelve months from the fifth month after the fiscal-year-end are reported at Panel B, C, and D respectively. T-statistics are shown below the return figures.

Panel A-1: Sorted first by *SYNCH*, then by *SUE* (drift from the current period earnings announcement date (EAD0) to the subsequent earnings announcement date (EAD1))

		SUE				
	Port rank	0	1	2	3	(3-0)
	0	-0.0267	-0.016	0.0172	0.0354	0.0621
		-1.49	***5.05***	***7.47***	***7.52***	***13.49***
	1	-0.0202	-0.0036	0.0176	0.0456	0.0456
SYNCH		*-1.77*	***5.03***	***4.83***	***6.47***	***12.58***
	2	-0.0124	0.0001	0.0080	0.0260	0.0384
		-2.47	***4.32***	*5.98*	*6.18*	***9.12***
	3	-0.0074	0.0008	0.0072	0.0170	0.0244
		-2.58	***4.88***	***5.18***	***6.08***	***5.89***
	(0-3)	-0.0192	-0.0024	0.0100	0.0184	0.0377
		5.40	*-0.71*	***2.62***	***4.12***	***7.28***

Panel A-2: Sorted first by SYNCH, then by SUE (three-day drift surrounding the subsequent earnings announcement date (EAD1))

		SUE				
	Port rank	0	1	2	3	(3-0)
	0	-0.0005	0.0037	0.0115	0.0116	0.0121
		-0.62	***5.17***	***6.94***	***12.81***	***10.45***
	1	-0.0004	0.0045	0.0124	0.0089	0.0093
SYNCH		*-0.54*	***5.02***	***2.34***	***11.62***	***8.54***
	2	-0.0012	0.0027	0.0059	0.0072	0.0084
		-1.79	***4.56***	***4.86***	***10.60***	***8.83***
	3	-0.0005	0.0019	0.0035	0.0048	0.0053
		-0.93	***3.22***	***4.92***	***7.86***	***7.03***
	(0-3)	-0.0000	0.0018	0.0080	0.0068	0.0068
		-0.03	***2.04***	***4.27***	***7.01***	***5.28***

Panel B: Sorted first by *SYNCH* and then by *V/P*

		V/P				
	Port rank	0	1	2	3	(0-3)
	0	0.0091	0.0100	-0.0012	-0.0093	0.0184
		5.57	***4.84***	*-1.18*	***-7.60***	***7.57***
	1	0.0084	0.0053	-0.0029	-0.0096	0.0180
SYNCH		***5.20***	***5.23***	***-2.91***	***-8.74***	***8.02***
	2	0.0076	0.0032	-0.0021	-0.0086	0.0162
		4.80	***3.60***	***-2.30***	***-8.56***	***7.35***
	3	0.0071	0.0025	-0.0014	-0.0062	0.0133
		4.89	***2.90***	*-1.65*	***-6.03***	***6.55***
	(0-3)	0.0020	0.0025	0.0002	-0.0031	0.0051
		1.23	***2.02***	*0.18*	***-2.40***	***2.49***

Panel C: Sorted first by *SYNCH* and then by *SACCRUAL*

		SACCRUAL				
	Portfolio	0	1	2	3	(0-3)
	0	0.0042	0.0037	0.0002	-0.0026	0.0068
		4.27	***5.54***	*0.32*	***-3.95***	***5.90***
	1	0.0016	0.0007	0.0003	-0.0034	0.0050
SYNCH		***1.87***	*1.20*	*0.65*	***-4.88***	***4.51***
	2	0.0006	0.0004	0.0001	-0.0035	0.0041
		0.93	*1.00*	*0.10*	***-5.26***	***4.39***
	3	0.0002	0.0004	0.0000	-0.0018	0.0020
		0.22	*0.75*	*0.10*	***-2.65***	***2.18***
	(0-3)	0.0040	0.0033	0.0002	-0.0008	0.0048
		3.20	***3.66***	*0.19*	*-0.80*	***3.55***

Panel D: Sorted first by *SYNCH* and then by *SNOA*

		SNOA				
	Portfolio	0	1	2	3	(0-3)
	0	0.0073	0.0021	0.0003	-0.0043	0.0116
		6.32	***3.09***	*0.48*	***-6.04***	***7.92***
	1	0.0037	0.0015	-0.0004	-0.0056	0.0093
SYNCH		***4.10***	***2.51***	*-0.73*	***-8.16***	***7.48***
	2	0.0031	0.001	-0.0009	-0.0055	0.0086
		4.39	*1.84*	*-1.76*	***-8.68***	***8.63***
	3	0.0023	0.0006	-0.0003	-0.0038	0.0061
		3.80	*1.25*	*-0.68*	***-5.30***	***7.31***
	(0-3)	0.0050	0.0015	0.0006	-0.0005	0.0055
		3.75	*1.63*	*0.82*	*-0.48*	***3.55***

Table IV

Synchronicity and Earnings Informativeness

MSYNCH: average of *SYNCH* over the past 15 years, in which $SYNCH = \log(\frac{R^2_{adj}}{1-R^2_{adj}})$, where R^2_{adj} is adjusted R-square statistic from within-firm-fiscal-year regressions of the market model using weekly stock returns data that also include industry returns. *CERC*: the stock return response coefficient of current-period earnings changes in regression (12) estimated over the past 15 years (same rolling window approach for *FERC*, *CREL*, and *FREL*): $r_t = a + b_0\Delta E_t + \sum_\tau b_\tau \Delta E_{t+\tau} + \sum_\kappa c_\kappa r_{t+\kappa} + \mu_t$, namely, the estimate of b_0. *FERC*: the sum of stock return response coefficients of future earnings changes in regression (12), namely, $\sum_\tau \hat{b}_\tau$. *CREL*: value relevance of current earnings, measured as the explanatory power of current-period earnings changes on current-period stock returns, namely, the R-square statistic from the regression $r_{i,t} = a_i + b_i\Delta E_{i,t} + \mu_{i,t}$. *FREL*: value relevance of future earnings, measured as the incremental explanatory power of future-period earnings changes on current period stock returns, namely, $FREL \equiv R^2_{r_t = a + b_0\Delta E_t + \sum_\tau b_\tau \Delta E_{t+\tau} + \sum_\kappa c_\kappa r_{t+\kappa} + \mu_t} - R^2_{r_t = a + b_0\Delta E_t + \mu_t}$.

Variable	*MSYNCH* deciles	1	2	3	4	5	6	7	8	9	10	(1-10)	t-stat for (1-10)
MSYNCH	Mean	-3.94	-2.47	-1.82	-1.36	-0.96	-0.58	-0.25	0.10	0.57	1.28	-5.22	
	Median	-4.25	-2.79	-2.24	-1.89	-1.57	-1.28	-0.96	-0.57	-0.07	0.46	-4.72	
CERC	Mean	3.82	4.06	3.96	3.70	4.14	4.27	4.02	3.76	3.43	2.61	1.21	***5.44***
	Median	3.54	3.86	3.84	3.69	3.90	4.35	3.74	3.63	3.44	2.57	0.97	
FERC	Mean	2.14	2.41	2.86	2.57	3.49	3.71	4.88	5.34	4.66	4.70	-2.56	***-5.39***
	Median	2.06	2.05	2.57	2.83	3.10	3.94	4.94	4.92	4.21	4.62	-2.56	
CREL	Mean	5.7%	5.6%	5.6%	4.9%	4.3%	4.8%	3.8%	3.5%	3.3%	2.9%	2.8%	***7.43***
	Median	5.8%	5.6%	4.9%	5.2%	4.5%	5.2%	3.9%	4.2%	3.1%	2.9%	2.9%	
FREL	Mean	2.8%	2.0%	3.2%	3.9%	4.8%	5.1%	5.8%	6.9%	5.2%	5.9%	-3.1%	***-2.57***
	Median	2.8%	3.0%	3.5%	3.6%	4.8%	5.6%	6.5%	7.1%	5.4%	5.7%	-2.9%	

Table V

Synchronicity and Earnings Attributes

MSYNCH: average of *SYNCH* over the past 15 years, in which $SYNCH = \log(\frac{R^2_{adj}}{1 - R^2_{adj}})$, where R^2_{adj} is adjusted R-square statistics from within-firm-fiscal-year regressions of the market model using weekly stock returns data that also includes industry returns. *SEARN*: earnings before extraordinary items deflated by total assets at the beginning of the year. *SACCRUAL*: total accruals deflated by total assets at the beginning of the year. *SCF*: the difference between *SEARN* and *SACCRUAL*. *STD_SEARN* (*STD_SACCRUAL, STD_SCF*): standard deviation of *SEARN* (*SACCRUAL*, *SCF*) of each firm calculated over fifteen-year rolling windows. *EQ_DD*: the measure of accrual quality following Dechow and Dichev (2002). *PERSIST*: earnings persistence, measured as (-1* $\hat{\beta}_{1,i}$), where $\hat{\beta}_{1,i}$ is estimated from the regression (9): $EPS_{i,t} = \beta_{0,i} + \beta_{1,i} EPS_{i,t-1} + \eta_{i,t}$ over fifteen-year rolling windows. *PREDICT*: earnings predictability, defined as $\sigma(\hat{\eta}_{i,t})$, where $\hat{\eta}_{i,t}$ is the estimated residual from regression (9) over fifteen-year rolling windows. *SMOOTH*: the ratio of a firm's standard deviation of net income before extraordinary items, to its standard deviation of cash flows from operations, namely, $SMOOTH_{i,t} = \sigma(NIBE_{i,t}) / \sigma(CFO_{i,t})$, calculated over fifteen-year rolling windows. *MV*: market value, defined as stock price per share*number of shares outstanding at the end of each fiscal year. Fama-MacBeth t-statistics are shown below the estimated coefficients.

Panel A: Decomposition of Earnings into Accruals and Cash Flow Components

Variable	*SYNCH* deciles	1	2	3	4	5	6	7	8	9	10	(1-10)	t- t-stat for (1-10)
SYNCH deciles in the previous year													
SEARN	Mean	0.06	0.04	0.06	0.08	0.09	0.10	0.11	0.12	0.13	0.14	-0.09	***-10.23***
	Median	0.04	0.05	0.08	0.09	0.09	0.09	0.11	0.12	0.13	0.13	-0.09	
SACCRUAL	Mean	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.01	*-0.61*
	Median	-0.03	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.04	0.00	
SCF	Mean	0.09	0.07	0.08	0.10	0.11	0.12	0.12	0.13	0.15	0.17	-0.08	***-8.79***
	Median	0.08	0.09	0.10	0.11	0.11	0.11	0.13	0.14	0.15	0.17	-0.09	
MSYNCH deciles													
STD_SEARN	Mean	0.031	0.030	0.028	0.023	0.026	0.020	0.015	0.011	0.009	0.004	0.027	***4.93***
	Median	0.030	0.028	0.027	0.020	0.017	0.017	0.012	0.007	0.006	0.003	0.027	
STD_SACCRUAL	Mean	0.018	0.017	0.017	0.014	0.014	0.013	0.011	0.009	0.008	0.005	0.013	***10.72***
	Median	0.018	0.017	0.017	0.014	0.013	0.013	0.011	0.008	0.007	0.004	0.014	
STD_SCF	Mean	0.034	0.031	0.031	0.025	0.027	0.023	0.018	0.014	0.012	0.007	0.027	**5.63**
	Median	0.033	0.031	0.032	0.023	0.021	0.020	0.016	0.012	0.008	0.006	0.027	

Table V (Cont'd)

Panel B: Earnings Attributes

Variable	*MSYNCH* deciles	1	2	3	4	5	6	7	8	9	10	(1-10)	t-stat for (1-10)
EQ_DD	Mean	0.003	0.003	0.003	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.002	***8.65***
	Median	0.003	0.003	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.002	
PERSIST	Mean	-0.44	-0.45	-0.46	-0.46	-0.47	-0.49	-0.50	-0.51	-0.51	-0.53	0.087	***7.41***
	Median	-0.45	-0.44	-0.46	-0.46	-0.47	-0.49	-0.51	-0.51	-0.51	-0.53	0.085	
PREDICT	Mean	0.063	0.065	0.061	0.053	0.050	0.044	0.039	0.037	0.036	0.030	0.033	***8.61***
	Median	0.060	0.057	0.054	0.047	0.049	0.039	0.035	0.031	0.029	0.026	0.034	
SMOOTH	Mean	0.65	0.67	0.64	0.59	0.59	0.57	0.52	0.51	0.52	0.52	0.13	***7.07***
	Median	0.65	0.68	0.61	0.57	0.60	0.51	0.51	0.46	0.44	0.50	0.15	

Table V (Cont'd)

Panel C: Multivariate Regression Analysis

	Intercept	*EQ_DD*	*PERSIST*	*PREDICT*	*SMOOTH*	*CERC*	*FERC*	*CREL*	*FREL*	*MV*	*Adj. R^2*
Model1	-0.946	-51.485									1.5%
	-4.82	***-6.10***									
Model2	-1.128		-0.221								0.4%
	-5.87		***-8.23***								
Model3	-0.769			-6.222							3.3%
	-3.66			***-7.88***							
Model4	-0.919				-0.194						0.7%
	-4.48				***-5.48***						
Model5	-1.021					0.005	-0.005				0.3%
	-5.32					***4.09***	***-6.30***				
Model6	-1.007							0.389	-0.085		0.3%
	-5.19							***6.26***	***-3.27***		
Model7	-0.800	-4.562	-0.107	-5.700	-0.018	0.008	-0.003				3.9%
	-3.69	*-1.15*	***-5.17***	***-7.30***	*-0.79*	***6.18***	***-5.23***				
Model8	-0.805	-4.600	-0.102	-5.668	-0.014			0.365	-0.057		3.9%
	-3.70	*-1.13*	***-5.13***	***-7.04***	*-0.63*			***5.97***	***-2.43***		
Model9	-0.917	-4.966	-0.082	-4.712	-0.028			0.303	-0.056	0.001	7.1%
	-4.26	*-1.31*	***-3.78***	***-6.55***	*-1.21*			***5.68***	***-2.47***	***8.95***	

Table VI

Synchronicity and Distress Risks

LOSS: an indicator variable that takes the value of one if the concerned firm incurs a loss in the year and zero otherwise. *Z-SCORE*: calculated as 1.2*(working capital/assets) + 1.4*(retained earnings/assets)+3.3*(EBIT/assets)+0.6*(MV/liabilities)+sales/assets. *ZSCOREN*=(-1)*Z-SCORE. *BSMPROB*: a market-information-based bankruptcy risk measure, derived following Hillegeist et al. (2004). *EQ_DD*: the measure of accrual quality following Dechow and Dichev (2002). *PERSIST*: earnings persistence, measured as (-1* $\hat{\beta}_{1,i}$), where $\hat{\beta}_{1,i}$ is estimated from the regression (9): $EPS_{i,t} = \beta_{0,i} + \beta_{1,i} EPS_{i,t-1} + \eta_{i,t}$ over ten-year rolling windows. *PREDICT*: earnings predictability, defined as $\sigma(\hat{\eta}_{i,t})$, where $\hat{\eta}_{i,t}$ is the estimated residual from regression (9) over fifteen-year rolling windows. *SMOOTH*: the ratio of a firm's standard deviation of net income before extraordinary items to its standard deviation of cash flows from operations, namely, $SMOOTH_{i,t} = \sigma(NIBE_{i,t}) / \sigma(CFO_{i,t})$, calculated over fifteen-year rolling windows. *CREL*: value relevance of current earnings, measured as the explanatory power of current-period earnings changes on current-period stock returns, namely, the R-square statistic from the regression $r_{i,t} = a_i + b_i \Delta E_{i,t} + \mu_{i,t}$. *FREL*: value relevance of future earnings, measured as the incremental explanatory power of future-period earnings changes on current period stock returns, namely, $FREL \equiv R^2_{r_t = a + b_0 \Delta E_t + \sum_\tau b_\tau \Delta E_{t+\tau} + \sum_\kappa c_\kappa r_{t+\kappa} + \mu_t} - R^2_{r_t = a + b_0 \Delta E_t + \mu_t}$. *MV*: market value, defined as stock price per share*number of shares outstanding at the end of each fiscal year. *ZSCOREN*=(-1)*Z-SCORE. Fama-Macbeth t-statistics are shown below the estimated coefficients.

Panel A: Distress Proxies

Variables	*SYNCH* Deciles	1	2	3	4	5	6	7	8	9	10	(1-10)	t-stat for (1-10)
LOSS	Mean	23.6%	25.5%	21.4%	18.9%	17.3%	14.4%	11.3%	9.3%	8.4%	5.1%	18.5%	***8.81***
	Median	26.9%	24.9%	20.3%	17.1%	17.2%	16.1%	11.1%	7.2%	4.8%	3.4%	23.5%	
ZSCOREN	Mean	-2.41	-2.30	-2.61	-2.74	-2.92	-3.14	-3.30	-3.58	-3.78	-4.27	1.86	***6.39***
	Median	-2.60	-2.62	-2.71	-2.74	-2.80	-3.11	-3.50	-3.72	-4.11	-4.58	1.99	
BSMPROB	Mean	6.30%	6.80%	5.40%	4.30%	3.20%	2.60%	1.90%	1.60%	1.50%	0.60%	5.7%	***7.72***
	Median	5.90%	5.40%	4.50%	3.70%	3.00%	1.90%	1.40%	0.80%	0.40%	0.30%	5.6%	

Table VI (Cont'd)

Panel B: Multivariate Regression Analysis

	Intercept	*EQ_DD*	*PERSIST*	*PREDICT*	*SMOOTH*	*CREL*	*FREL*	*LOSS*	*ZSCOREN*	*BSMPROB*	*MV*	Mean *Adj. R^2*
Model 1	-0.923							-0.846				2.5%
	-4.53							***-11.54***				
Model 2	-1.357								-0.091			2.2%
	-7.57								***-11.91***			
Model 3	-0.940									-4.451		3.4%
	-4.65									***-10.57***		
Model 4	-1.082							-0.508	-0.050	-3.274		5.3%
	-5.36							***-9.62***	***-9.34***	***-9.74***		
Model 5	-1.153							-0.433	-0.025	-3.112	0.001	10.6%
	-5.79							***-8.51***	***-5.86***	***-9.66***	***9.40***	
Model 6	-1.035	1.573	-0.078	-3.012	0.002	-0.262	0.032	-0.334	-0.016	-2.842	0.001	11.6%
	-4.71	*0.31*	***-3.69***	***-4.61***	*0.08*	***-5.38***	*1.27*	***-7.77***	***-3.52***	***-10.00***	***9.21***	

Table VII

Synchronicity and Disclosure

AIMR: within-industry ranks of the analysts' disclosure scores published by the Association of Investment Management Research. *MV*: market value, defined as stock price per share*number of shares outstanding at the end of each fiscal year. Fama-Macbeth t-statistics are shown below the estimated coefficients.

	Intercept	*AIMR*	*MV*	*Adj.* R^2
Model 1	-0.081	-0.202		0.06%
	-0.26	***-2.40***		
Model 2	-0.339	-0.106	0.000	7.97%
	-1.11	*-1.27*	***6.30***	