Financial Anomalies and Information Uncertainty

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We examine whether rational investor responses to information uncertainty (*IU*) explain properties of and returns to several financial anomalies (post-earnings announcement drift, value-glamour, and accruals anomalies). Consistent with a rational learning explanation, we find that: (1) higher *IU* signals have more muted initial market reactions; (2) extreme anomaly portfolios are characterized by securities with higher *IU* than non-extreme portfolios; (3) within the extreme anomaly portfolios, high *IU* securities are more prevalent and earn larger abnormal returns than low *IU* securities; and (4) the abnormal returns to high *IU* securities converge to the abnormal returns to low *IU* securities as the post-portfolio formation period lengthens. Further tests show that prior evidence of greater anomaly profitability for higher idiosyncratic volatility securities is largely explained by these securities having greater information uncertainty.

Draft: April 2004

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1. Introduction

Our study builds on prior research that attempts to explain the existence of financial anomalies. By financial anomaly we mean a systematic pattern in long term stock returns following a public investment signal (such as earnings) which can be exploited to generate returns over and above the expected return as measured by the one-factor capital asset pricing model (CAPM) or its three-factor or four-factor extension. Within this literature, research has explored irrational and rational explanations for the existence of abnormal returns to trading strategies. The literature on irrationality posits behavioral explanations for anomalies (see Barberis and Thaler [2004] for an overview) which generally argue that one or more cognitive processing biases – such as representativeness and conservatism – lead to the observed abnormal returns patterns.[1] However, in direct out-of-sample tests, Chan, Frankel and Kothari [2003] find little support for explanations based on representativeness bias.

Within the literature examining rational explanations for anomalies, research has focused on rational investor processing of incomplete information structures (e.g., Merton [1987], Timmerman [1993], Kurtz [1994], Morris [1996], and Lewellen and Shanken [2002]). This body of work shows that uncertainty (or other imperfections, such as partial information) about the information structure can lead to the appearance of risk premiums or asset pricing anomalies. That is, faced with valuation parameter uncertainty, investors rationally price stocks in a way that leads to the appearance of deviations from market efficiency. Of particular relevance to our study is Brav and Heaton's [2002] structural uncertainty model in which fully Bayesian investors face uncertainty about whether there has been a shift in the payoff structure of investments. These investors' estimates of the valuation parameter will appear to underweight (that is, under-react to) information signals that arrive just after a structural shift has occurred, because their estimates reflect uncertainty about whether there has in fact been a change. As we

[1] Representativeness occurs when subjects over-weight recent pieces of evidence, ignoring base rate information. Conservatism is the opposite: subjects under-weight recent information, placing excessive weight on base rates.

discuss in more detail in section 2, fully Bayesian investors will also place less weight on signals that are characterized by greater information uncertainty (that is, lower precision or quality). As this uncertainty is resolved, investors increase their weights on the information in the original signal, resulting in subsequent movements in asset prices. The abnormal returns resulting from such price movements diminish as uncertainty is resolved. We refer to this effect as "rational learning," in the sense that investors appropriately alter their estimates of the valuation parameter of the payoff structure in light of new information.[2]

In this paper, we test four predictions derived from the rational learning explanation. First, investors should respond less, initially, to investment signals characterized as having high information uncertainty than to investment signals of low information uncertainty. Second, if information uncertainty is important in explaining financial anomalies, securities included in extreme anomaly portfolios (i.e., the ones that constitute the trading strategy) should have higher average information uncertainty than securities in non-extreme portfolios. Third, a disproportionate amount of the abnormal returns to extreme anomaly portfolios should be concentrated in stocks with high information uncertainty; that is, low information uncertainty stocks in the extreme anomaly portfolios should not generate large (in magnitude) abnormal returns. Fourth, as uncertainty about the investment signal is resolved over time, the magnitude of high information uncertainty securities' abnormal returns should decline, converging in magnitude to the abnormal returns of low information uncertainty securities.

We test these predictions for three classes of financial anomalies: post earnings announcement drift (e.g., Bernard and Thomas [1989; 1990]; Abarbanell and Bernard [1992]; Chan, Jegadeesh, and Lakonishok [1996]); value-glamour strategies (e.g., Lakonishok, Shleifer and Vishny [1994]), and an accruals strategy (Sloan [1996]; Chan, Chan, Jegadeesh and Lakonishok [2001]). Our main tests use Dechow and Dichev's [2002] measure of earnings quality as the proxy for information uncertainty (*IU*). This measure captures the mapping of earnings into cash flows: the weaker the mapping, the poorer is the

[2] Lu's [2004] model of information diffusion yields predictions similar to those in Brav and Heaton [2002]. However, Lu does not specify the mechanism through which information flows into prices.

information quality of earnings and, therefore, the greater is the uncertainty of the earnings signal.[3] We focus on an earnings-based measure of information uncertainty because the anomalies we examine are linked to earnings and/or cash flow information: explicit links exist for post earnings announcement drift, price-earnings, price-cash flow, and total accruals, while a strong implicit link exists for book-to-market given that, for most firms, the largest component of book value of equity is retained earnings.

Our findings are consistent with all four predictions. Consistent with our first hypothesis, we document more muted investor responses to high *IU* investment signals. Specifically, we find significantly (at the 0.001 level) lower response coefficients relating unexpected announcement returns to the unexpected earnings revealed in quarterly earnings announcements, when the announcements are made by firms with higher information uncertainty.

Tests of our second hypothesis investigate whether the ranking of the investment signal is correlated with its *IU*. Moving from the top portfolios of the ranked signal to the bottom portfolios, we document a U-shaped pattern in *IU*: stocks in the extreme portfolios have significantly (at the 0.001 level) higher *IU* than stocks in the non-extreme portfolios. In addition, within each extreme portfolio, the incidence of securities with high information uncertainty (High *IU*) is generally significantly (at the 0.001 level) greater than the incidence of securities with low information uncertainty (Low *IU*). We interpret the U-shaped pattern as indicating a separation between the *quality* of the investment signal (i.e., its information uncertainty) and the nature of the news carried by the signal. That is, information uncertainty is associated with extreme realizations of investment signals, abstracting from the favorable or unfavorable information conveyed by the signal.

Our third hypothesis predicts that a disproportionate amount of the returns to trading strategies is associated with High *IU* stocks. To test this prediction, we hold the anomaly portfolio constant and examine whether long/short anomaly positions in High *IU* securities yield larger abnormal returns than

[3] We do not investigate the source(s) of information uncertainty, or distinguish between intrinsic uncertainty that is inherent in firms' business models and their operating environments, and management-induced uncertainty that is due to unintentional or intentional recognition and measurement errors. For the purposes of our investigations, only the existence and magnitude of information uncertainty matter, not its source.

equivalent positions in Low *IU* stocks. Results are consistent with the hypothesis. For example, for the post earnings announcement drift strategy, the average four-factor abnormal return is 76 basis points (bp) per month for the High *IU* securities versus -19 bp for the Low *IU* securities; for the book-to-market strategy, the mean abnormal return is about 67 bp per month for High *IU* securities versus -0.01 bp for Low *IU* securities. The finding that High *IU* securities generate larger abnormal returns than Low *IU* securities is consistent across anomalies and across measures of abnormal returns.

Fourth, we find that over the 36 months following portfolio formation, abnormal returns to High *IU* securities converge to the magnitude of abnormal returns to Low *IU* stocks. The protracted period over which abnormal returns persist, but diminish, for High *IU* securities is consistent with the argument that investors require time to resolve the greater uncertainty for these stocks. Specifically, as information uncertainty diminishes, so too does the abnormal return.

Finally, we link our results to prior evidence showing that idiosyncratic returns volatility predicts differential anomaly profitability (e.g., Ali, Hwang and Trombley [2003]; Mendenhall [2005]). Building on O'Hara's [2003] suggestion that information risk provides an explanation for why idiosyncratic volatility can matter in asset pricing studies, we hypothesize that *IU* is a more primitive variable than idiosyncratic volatility; therefore, we expect *IU* has stronger and more consistent effects than does idiosyncratic volatility. Consistent with this prediction, we find that: (i) idiosyncratic volatility does not consistently predict the profitability of asset pricing anomalies (the profitability of the cash-flow-to price and earnings-to-price anomalies is not significantly associated with idiosyncratic volatility), whereas *IU* produces consistent results across all anomalies; and (ii) when we orthogonalize idiosyncratic volatility with respect to *IU*, the effect of idiosyncratic volatility diminishes (or disappears altogether) for four of the five anomalies.

The rest of the paper is organized as follows. The next section develops hypotheses linking properties of the financial anomalies to predictable effects of information uncertainty, and describes our measure of information uncertainty. Section 3 reports our main tests, section 4 develops tests of the role of idiosyncratic returns volatility, section 5 reports sensitivity analyses, and section 6 concludes.

2. *Hypotheses and Measuring Information Uncertainty*

In this section, we begin by detailing our hypotheses concerning the relation between information uncertainty and financial anomalies (section 2.1). We follow this discussion with a description of how we measure information uncertainty (section 2.2).

2.1. Predictions concerning rational learning

To maximize the power of our tests, we focus on contexts where abnormal returns are linked to public information signals that have the appearance of being under-utilized by market participants. We emphasize these contextual features because they are consistent with the rational learning explanation which argues that investors rationally place less weight on imprecise investment signals, giving rise to abnormal returns over the period during which the information uncertainty is resolved. Anomalies based on accounting signals exhibit these features and, therefore, are prime candidates for examination.

We label the financial anomalies as under-reactions to the current signal (e.g., the earnings surprise or the value-glamour ratio). This labeling should not be confused with behavioral finance theories that argue that some anomalies are caused by *over-reactions* to past patterns. For example, Lakonishok, Shleifer and Vishny [1994] argue that firms with low earnings-price ratios have high past growth, and that investors over-react to this high past growth by naively extrapolating it into the future, causing price to become too high (and, therefore, the current earnings-price signal is low). That is, regardless of the reason for an apparent mispricing, our research concerns investor short- and long-term reactions to the *signal* indicating that current price is too high or too low, as evidenced by subsequent abnormal returns.

We consider three classes of financial anomalies: post earnings announcement drift (PEAD), accounting-based value-glamour strategies, and an accruals strategy. Descriptions of each anomaly, as well as summaries of research which document these anomalies, are reported in the Appendix. Briefly, each trading strategy takes positions based on extreme realizations of the investment signal, buying stocks with the most favorable signals and selling (shorting) stocks with the least favorable signals. The abnormal return to the long-short position measures the strategy's profitability. Prior studies document significant positive abnormal returns to these strategies over periods from six months to 36 months following portfolio formation.

We test four predictions related to information uncertainty as an explanation for these abnormal returns. The first concerns investors' *initial* reactions to the investment signal. Based on Bayesian decision theory research (e.g., DeGroot [1970]) that shows that loss-minimizing investors rationally place less weight on noisier (i.e., more uncertain) information, we expect to observe more muted initial market reactions to investment signals that have higher information uncertainty (Hypothesis 1).

The second hypothesis is based on the information uncertainty properties of securities with the most extreme values of the investment signals, i.e., the securities that yield the abnormal returns. Specifically, because we expect investors to assign low weights to high information uncertainty (High *IU*) signals irrespective of the content of the signal, we hypothesize that *both* the long position *and* the short position of each trading strategy are characterized by securities with High *IU* (Hypothesis 2).

Our third prediction focuses on differences in the abnormal returns to securities in the extreme anomaly portfolios, depending on whether the securities are characterized as High *IU* versus Low *IU*. We expect the abnormal return to High *IU* securities to exceed the abnormal return to Low *IU* securities in both the long and the short positions (Hypothesis 3). To understand why we expect such differences, it is important to note that the trading portfolios are formed based on *signed* magnitudes of investment signals and, unless information uncertainty is perfectly correlated across securities, information uncertainty will not be hedged by taking offsetting long and short positions in High *IU* (or Low *IU*) stocks.[4] That is, to the extent information uncertainty is idiosyncratic and not state dependent, the information uncertainty of the long position will not offset the information uncertainty of the short position. Hence, only in the limiting case of perfect correlation of information uncertainty will the abnormal return to High *IU* securities equal the abnormal return to Low *IU* securities. Therefore, tests of Hypothesis 3 are necessarily

[4] Easley and O'Hara [2004] show that when information uncertainty is uncorrelated across securities, investors cannot diversify it. Further, even when information uncertainty is correlated across securities, investors can reduce, but never eliminate it, by diversification. Leuz and Verrecchia [2004] also show that information uncertainty cannot be diversified away.

joint tests that there is imperfect correlation of information uncertainty across securities and that abnormal returns to trading strategies are larger for signals with higher information uncertainty.

There is an additional, confounding factor at play. Prior research shows that high information risk securities have higher average returns (e.g., Easley, Hvidkjær and O'Hara [2002]; Francis, LaFond, Olsson and Schipper [2005]). These empirical findings are consistent with the predictions from the Easley and O'Hara [2004] and Leuz and Verecchia [2004] models, which show that information uncertainty commands a risk premium in the capital markets. It follows that High *IU* securities will have higher *expected* returns than low *IU* securities. Therefore, post-event reactions to High *IU* signals are likely affected by two forces. The first is investor learning about the signal, which gives rise to a subsequent reaction in the *same* direction as the initial signal; this effect will cause post-event stock price movements to be positive for favorable signals and negative for unfavorable signals. The second force is the greater risk and expected return associated with High *IU* signals; this effect will cause post-event stock price movements to be positive for both favorable and unfavorable signals.[5] Combining the two effects yields an unambiguous prediction of positive subsequent price movements for favorable High *IU* signals; for unfavorable High *IU* signals, the expected direction of the price movement depends on which effect dominates. Given that anomaly-based trading strategies intentionally select extreme signal values, we conjecture that the learning effect dominates the risk effect for unfavorable signals.[6]

Our fourth hypothesis links the magnitude of abnormal returns to the time period over which information uncertainty is resolved. We expect that as information uncertainty is resolved, the anomaly

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[5] Brown, Harlow and Tinic [1988] arrive at a similar prediction based on the argument that major surprises are followed by increased short-term uncertainty which commands a higher expected return. They validate this hypothesis for a sample of major news events (defined as events which have a single day price change of at least 2.5% in absolute value) for the 200 largest S&P firms; their post event window is the 60 days following the event. We note two differences between this evidence and anomaly studies. First, most anomaly research takes positions based on the sign and magnitude of the information signal itself, rather than the magnitude of the price response to the signal. Second, anomaly research typically takes positions with some lag after the signal release, and measures the trend in abnormal returns over longer periods (e.g., 6-12 months for PEAD, 12-36 months for value-glamour).

[6] Supporting this statement, a comparison of the two effects based on results in prior research suggests that the anomaly effect is larger in magnitude than the expected returns effect associated with information uncertainty. In particular, Francis, LaFond, Olsson and Schipper [2005] report an average expected returns effect of 90-225 bp per year. The average anomaly abnormal returns are generally substantially larger (800-1000 bp per year), e.g., Lakonishok, Shleifer and Vishny [1994], Bernard and Thomas [1990].

abnormal returns to High *IU* signals diminish, converging in magnitude to the anomaly abnormal returns to Low *IU* signals (Hypothesis 4).

Finally, we advance a fifth hypothesis that relates to prior researchers' finding that book-to-market anomaly returns and PEAD returns are larger for firms with higher idiosyncratic stock return volatility (Ali, Hwang and Trombley [2003]; Mendenhall [2005]). Viewing idiosyncratic returns volatility as an outcome measure of firm-specific information risk, we predict that idiosyncratic volatility is significantly associated with *IU*, and that idiosyncratic volatility loses some or all of its predictive power over anomaly profitability when we control for *IU* (Hypothesis 5). We develop the rationale and tests of this prediction more fully in section 4.

2.2. Measuring information uncertainty

Our measure of information uncertainty is based on Dechow and Dichev's [2002] model augmented (as suggested by McNichols [2002]) with the fundamental variables from the modified Jones model, namely, property plant and equipment (PPE) and change in revenues (all variables are scaled by average assets). Intuitively, this measure views cash flows as fundamental to investors, and focuses on the non-cash flow portion of accounting earnings: accruals. Information uncertainty is deemed high if accruals map poorly into cash flows (in current or surrounding time periods) or other firm fundamentals known to be associated with accruals (fixed assets and revenue changes). Technically, we regress working capital accruals on cash from operations in the current period, prior period and future period, as well as PPE and revenue changes. The unexplained portion of the variation in working capital accruals is an inverse measure of the quality of earnings; that is, a greater unexplained portion implies lower quality. Specifically, our *IU* metric is based on the residuals from the following model:

$$TCA_{j,t} = \phi_{0,j} + \phi_{1,j}CFO_{j,t-1} + \phi_{2,j}CFO_{j,t} + \phi_{3,j}CFO_{j,t+1} + \phi_{4,j}\Delta Rev_{j,t} + \phi_{5,j}PPE_{j,t} + \upsilon_{j,t} \qquad (1)$$

where $TCA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$ = total current accruals in year t,
$CFO_{j,t} = NIBE_{j,t} - TA_{j,t}$ = firm j's cash flow from operations in year t,[7]

[7] We calculate total accruals using information from the balance sheet and income statement (indirect approach). We use the indirect approach rather than the statement of cash flows because statement of cash flow data are not

$NIBE_{j,t}$ = firm j's net income before extraordinary items (Compustat #18) in year t,

$TA_{j,t} = (\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t})$ = firm j's total accruals in year t

$\Delta CA_{j,t}$ = firm j's change in current assets (Compustat #4) between year t-1 and year t,

$\Delta CL_{j,t}$ = firm j's change in current liabilities (Compustat #5) between year t-1 and year t,

$\Delta Cash_{j,t}$ = firm j's change in cash (Compustat #1) between year t-1 and year t,

$\Delta STDEBT_{j,t}$ = firm j's change in debt in current liabilities (Compustat #34) between year t-1 and year t,

$DEPN_{j,t}$ = firm j's depreciation and amortization expense (Compustat #14) in year t,

$\Delta Rev_{j,t}$ = firm j's change in revenues (Compustat #12) between year t-1 and year t,

$PPE_{j,t}$ = firm j's gross value of property, plant and equipment (Compustat #7) in year t,

We estimate equation (1) for each of Fama and French's [1997] 48 industry groups with at least 20 firms in year t. Consistent with the prior literature, we winsorize the extreme values of the distribution to the 1st and 99th percentiles. Annual cross-sectional estimations of (1) yield firm- and year-specific residuals, which form the basis for our information uncertainty metric: $IU_{j,t} = \sigma(\upsilon_j)_t$ is the standard deviation of firm j's residuals, $\upsilon_{j,t}$, calculated over years t-4 through t. Larger standard deviations of residuals indicate greater information uncertainty. Note that the five-year requirement and the lead and lag terms in equation (1) mean that the *IU* sample is limited to firms with seven years of data.[8] We use these firm- and –year-specific *IU* measures to proxy for the information uncertainty of the signal generated by the firm each year (or quarter, in the case of PEAD).

We calculate *IU* for all firms with available data for each fiscal year, *t*, 1970-2001. To ensure that the *IU* measure is available to the market, we use lagged *IU* values in our tests. That is, we assume that the year t *IU* metric is available to the market at the beginning of the fourth month following the end of fiscal year t+1 (this accounts for the *t+1* cash flow term in equation (1)). Table 1, Panel A reports the number of observations in each sample year. The number of firms ranges from about 1,100 to 1,450 in the early years to about 3,400 per year in the later years; on average, there are 2,612 firms per year and

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available prior to 1988 (the effective year of SFAS No. 95). We draw similar inferences (not reported) if we restrict our sample to post-1987 and use data from the statement of cash flows.

[8] As explained in more detail in section 5, our results are not sensitive to the measure of information uncertainty. We obtain qualitatively similar using an abnormal accruals measure that does not require a time series of data, and consequently does not incorporate a measure of the over-time volatility of unexplained accruals.

the pooled sample contains 83,598 firm-year observations. Panel B reports descriptive information about *IU* for the pooled samples. The mean (median) value of $IU = \sigma(\hat{v})$ is 0.0403 (0.0292); these values, measured relative to the standard deviation of 0.0360, indicate substantial cross-sectional variation in information uncertainty.

3. Empirical Tests and Results

We begin by replicating prior studies' tests of PEAD, value-glamour anomalies, and the accruals anomaly for *all* firms with the necessary data for the period 1971-2001, and, separately, for the samples of firms with data on *IU*, to ascertain whether the strategies yield similar results for these securities (section 3.1). While we generally find smaller abnormal returns to the trading strategies for the *IU* sample relative to the population, in all cases we document significant positive abnormal returns for both samples. Having shown this result, we turn to tests of our four main hypotheses concerning rational learning (section 3.2). We summarize the results in section 3.3.

3.1 Abnormal returns to financial anomalies

For each anomaly, we identify all observations with the necessary data to determine both the investment signal and the subsequent return to a portfolio strategy that exploits this signal. We evaluate abnormal returns by taking long positions in the stocks ranked in the top two deciles of the distribution of the signal and short positions in the stocks ranked in the bottom two deciles. (While the differences in abnormal returns become more pronounced if we use the top and bottom decile, inferences remain unchanged; similarly, inferences are not affected by using the top three and bottom three deciles.) Appendix A discusses the construction of the signals and the formation of signal portfolios. In general, portfolio construction follows prior anomaly research, and empirical results are consequently consistent with prior literature in this area. For all abnormal returns tests, we use calendar-time portfolio regressions (described next) to assess the magnitude and statistical significance of the abnormal returns.[9] We

[9] There is a methodological debate about the most appropriate way to evaluate abnormal returns over long intervals. Barber and Lyon [1997] and Kothari and Warner [1997] show that commonly used methods, such as buy-and-hold

measure abnormal returns relative to three asset pricing models: a standard CAPM model, the three-factor model (Fama and French [1993]), and a four-factor model, which adds a returns momentum factor to the three-factor model (Carhart [1997]). Our purpose in presenting multiple measures of abnormal returns is to examine whether results are sensitive to controls for size, growth, and returns momentum. We do not take a stance on which is the "true" asset pricing model – rather, our intent is to ensure that we are not merely re-discovering empirical regularities documented in prior literature. By including returns momentum as a control, we can also ascribe abnormal returns effects uniquely to accounting information uncertainty, as opposed to returns-relevant information emanating from the stock market.

Each month *m*, we calculate the average abnormal return to the p = long (L) and short (S) portfolios. For the CAPM-based abnormal return, the average abnormal return equals the intercept from regressing the excess return for the *p*'th portfolio on the excess market return for month *m*:

$$R_{p,m} - R_{F,m} = \alpha_p^{CAPM} + \beta_p RMRF_m + \varepsilon_{p,m}^{CAPM} \qquad (2a)$$

where $R_{p,m}$ is the return to portfolio p in month m, $R_{F,m}$ is the monthly risk-free rate, and $RMRF_m$ is the monthly excess market return.

The three-factor abnormal return to portfolio p equals the intercept from regressing the mean excess return for the *p*'th portfolio on the excess market return, the monthly return of a factor-mimicking portfolio for size (SMB_m), and the monthly return of a factor- mimicking portfolio for book-to-market (HML_m):

$$R_{p,m} - R_{F,m} = \alpha_p^{3f} + b_p RMRF_m + s_p SMB_m + h_p HML_m + \varepsilon_{p,m}^{3f} \qquad (2b)$$

abnormal returns, are mis-specified. Fama [1998] argues that calendar-time abnormal monthly returns are strongly preferred because: (i) the portfolio variance automatically accounts for cross-correlations of abnormal returns; (ii) relative to buy-and-hold abnormal returns, average monthly abnormal returns are less susceptible to problems with the model of expected return; and (iii) the distribution of monthly returns is well-approximated by a normal distribution, allowing for classical statistical inference, whereas longer horizon returns are skewed, requiring special statistical corrections. While Loughran and Ritter [2000] argue that calendar-time abnormal monthly returns have low power, Mitchell and Stafford [2000] show that monthly calendar-time regressions have sufficient power to detect economically interesting abnormal returns, and have more power than statistically-corrected buy-and-hold returns. Based on the extant evidence, we use calendar-time portfolio regressions based on monthly returns because this procedure is robust to methodological concerns. The potential price we pay for this choice is lower statistical power, which works against finding results.

The four-factor abnormal return to portfolio *p* equals the intercept from regressing the mean excess return for the *p*'th portfolio on the excess market return, *SMB*, *HML* and the returns to a returns momentum factor, PM_m.[10]

$$R_{p,m} - R_{F,m} = \alpha_p^{4f} + b_p RMRF_m + s_p SMB_m + h_p HML_m + m_p PM_m + \varepsilon_{p,m}^{4f} \tag{2c}$$

Finally, the CAPM, three-factor, and four-factor abnormal returns to the long-short (*LS*) positions are the estimated intercepts from equations (2d), (2e) and (2f), respectively:

$$(R_L - R_S)_m = \alpha_{LS}^{CAPM} + \beta_{LS} RMRF_m + \varepsilon_{LS,m}^{CAPM} \tag{2d}$$

$$(R_L - R_S)_m = \alpha_{LS}^{3f} + b_{LS} RMRF_m + s_{LS} SMB_m + h_{LS} HML_m + \varepsilon_{LS,m}^{3f} \tag{2e}$$

$$(R_L - R_S)_m = \alpha_{LS}^{4f} + b_{LS} RMRF_m + s_{LS} SMB_m + h_{LS} HML_m + m_{LS} PM_m + \varepsilon_{LS,m}^{4f} \tag{2f}$$

Table 2 shows the average monthly abnormal returns for each anomaly. For all but the PEAD strategy, the abnormal returns are measured over 1971-2001;[11] the interval for PEAD is restricted to the period 1982-2001 where we have analyst forecast data. The columns labeled Unrestricted Sample show abnormal returns unconditional on the firm having data on *IU*; the columns labeled "*IU* Sample" show abnormal returns for the observations where we also have data on *IU*. We report the results for the Unrestricted Sample to ensure that we find the same empirical regularities as prior research. (Because prior studies differ in terms of time period examined as well as portfolio formation and estimation procedures, we do not seek to replicate a particular prior study's results.)

Predictably, most of the trading strategies show negative abnormal returns to the portfolios in which we take short positions and positive abnormal returns to the long positions. CAPM, three-factor and four-factor abnormal returns to the combined long-short positions are significantly positive (at the 0.001 level), with four-factor abnormal returns generally smaller in absolute magnitude than three-factor abnormal returns, which are themselves smaller than CAPM abnormal returns. The profitability of the

[10] *SMB*, *HML* and *PM* are from K. French's web site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.
[11] We start in April of 1971 because the majority of firms have fiscal year ends in December. This yields 369 months of returns data, April 1971-December 2001.

trading strategies for the *IU* Sample is also generally smaller than the profitability for the Unrestricted Sample. Hereafter, results for an anomaly refer to the abnormal return of the combined long-short position unless noted.

Turning first to PEAD, we document abnormal returns of 45-72 bp per month or 5.4%-8.6% on a yearly basis, for the Unrestricted Sample, and 35-62 bp per month or 4.2%-7.5% per year for the *IU* Sample. These returns are roughly similar to those documented in prior studies. For example, Bernard and Thomas [1990, Table 2] report an 8.6% four-quarter cumulative abnormal return for the period 1974-1986; for the 1990s, Johnson and Schwartz [2000] find that the four-quarter cumulative abnormal return declined to about 5.7%. Abarbanell and Bernard [1992] report significant abnormal returns in two quarters using an analyst specification, for a combined abnormal return of about 6%.

Turning to the value-glamour anomalies, the book-to-market strategy produces abnormal returns of between 61-107 bp per month (7.4%-12.8% per year).[12] In comparison, for the *IU* Sample, the abnormal returns to this strategy range between 42 and 71 bp per month (5.0% to 8.5% per year). The cash flow-to-price and earnings-to-price specifications show abnormal returns for the Unrestricted Sample ranging between 57-87 bp per month (6.8%-10.4% per year); these compare to 32-73 bp per month (3.8%-8.8% per year) for the *IU* sample. These returns are similar to the annualized value-glamour CAPM abnormal returns reported by Lakonishok, Schleifer and Vishny [1994] for the period 1968-1990: 7.6% for earnings-price (5.4% size-adjusted); 11% for cash flow-to-price (8.8% size-adjusted); and 10.5% for book-to-market (7.8% size-adjusted).[13]

Finally, for the accruals anomaly, the Unrestricted Sample shows abnormal returns of 61-76 bp per month, nearly identical to the 67-71 bp per month for the *IU* sample. On an annualized basis, the

[12] Our finding of significant three-factor and four-factor based abnormal returns to the book-to-market strategy is consistent with prior research which documents significant abnormal returns to extreme book-to-market portfolios even when the pricing regression includes a book-to-market factor in calculating the benchmark for expected returns (see, e.g., Mitchell and Stafford [2000] for a discussion).

[13] There are numerous differences in how studies implement value-glamour strategies. For example, similar to Lakonishok, Schleifer and Vishny [1994], we exclude observations where the accounting signal (earnings, cash flows, book value of equity) is negative; it is not always clear how other studies treat these observations. As another example, our dynamic portfolio formation technique updates the accounting signals as of the fourth month following each firm's fiscal year end; other studies update only at a particular calendar month (Lakonishok et al. update in April; Fama and French [1993] update in June).

abnormal return to the accruals strategy (for both the Unrestricted Sample and *IU* Sample) is about 7-9%, and is similar to the 10.4% return documented by Sloan [1996].

3.2. Tests of Hypotheses 1-4

Our analysis of whether information uncertainty is associated with financial anomalies begins by investigating whether signals with higher information uncertainty have more muted immediate market responses (Hypothesis 1). We test H1 by examining whether the response coefficient relating unexpected returns to unexpected earnings news in firms' quarterly earnings announcements is smaller for firms with larger values of *IU*, i.e., $\gamma_2 < 0$ in equations (3a) and (3b):[14]

$$CAR(-1,0)_{j,q} = \gamma_0 + \gamma_1 UE_{j,q} + \gamma_2 UE \bullet DecileIU_{j,q} + \zeta_{j,q} \tag{3a}$$

$$CAR(-1,0)_{j,q} = \gamma_0 + \gamma_1 UE_{j,q} + \gamma_2 UE \bullet DecileIU_{j,q} + \gamma_3 Size_{j,q} + \gamma_4 Leverage_{j,q} + \gamma_5 Growth_{j,q} + \zeta_{j,q} \tag{3b}$$

where $CAR(-1,0)_{j,q}$ = cumulative 2-day market-adjusted return around firm j's quarter q earnings announcement;

$UE_{j,q}$ = unexpected earnings news revealed in firm j's quarter q earnings announcement, scaled by firm j's share price twenty days before the earnings announcement date. Expected earnings equal the consensus analyst forecast for quarter q.

$DecileIU_{j,q}$ = decile rank of *IU*; observations with the highest (lowest) values of *IU* are included in decile 10 (decile 1).

$Size_{j,q}$ = firm j's log of total assets, measured at the end of the fiscal year preceding quarter q's earnings announcement;

$Leverage_{j,q}$ = firm j's ratio of interest bearing debt to total assets measured at the end of the fiscal year preceding quarter q's earnings announcement;

$Growth_{j,q}$ = firm j's sales growth, measured as the percentage change between years t-1 and t.

We estimate equations (3a) and (3b) for each year using all observations with data on earnings announcement dates and unexpected earnings. Because of availability of analyst forecast data, the sample is restricted to the 20-year interval, 1982-2001.[15] Statistical inference is based on the time-series standard errors of the coefficient estimates across the quarterly regressions (Fama and Macbeth [1973]). Results,

[14] Equation (3b) includes firm size, financial leverage and growth, as these factors have been shown to be associated with the market reactions to earnings news.
[15] As discussed in section 5, results are not sensitive to using a time-series based earnings forecast to proxy for expected earnings.

reported in Table 3, show that there is a significantly smaller coefficient relating unexpected returns to unexpected earnings for stocks with higher information uncertainty. Specifically, $\gamma_2 < 0$ in both regressions, with t-statistics of –3.40 and –3.67. This finding of more muted immediate reactions to higher information uncertainty signals is consistent with H1.

Our second set of tests examines whether information uncertainty is concentrated in the extreme deciles of the ranked distribution of the signal underlying each anomaly (Hypothesis 2). Each month we calculate the mean value of *IU* for securities within each anomaly decile as well as for the difference between securities in the extreme and non-extreme deciles. Panel A, Table 4 reports the over-time average of the 369 mean values of *IU* by anomaly decile, and Figure 1 illustrates these data for PEAD, cash flow-to-price, and accruals signals. In all cases, we document a U-shaped pattern: stocks in the extreme anomaly deciles have higher *IU* than stocks in the moderate deciles. The rightmost columns of Panel A report comparisons of the mean *IU* of deciles 1, 2, 9 and 10 (the extreme portfolios) with the mean *IU* of deciles 3-8 (the moderate portfolios). The statistical significance of this difference is based on the standard error of the time series of 369 monthly differences. In all cases, the difference in *IU* is significantly positive, with t-statistics exceeding 29. The far right column reports the fraction of months (out of 369) where the mean *IU* in the extreme portfolios is higher than the mean *IU* in the moderate portfolios. For all anomalies, the results show an overwhelming preponderance of months (98% or more) where the extreme portfolios are characterized as having higher *IU* than the moderate portfolios. This evidence indicates that the difference in *IU* exists in virtually every period.

To probe whether the higher *IU* in the extreme deciles is pervasive across the securities in these portfolios, we rank observations from lowest *IU* to highest *IU*: the Low *IU* portfolio (deciles 1 and 2) contains stocks with the lowest information uncertainty, while the High *IU* portfolio (deciles 9 and 10) contains stocks with the highest information uncertainty. We then examine the frequency of Low *IU* versus High *IU* securities within the extreme anomaly portfolios. Because we rank on *IU* independent of the trading strategy – that is, we do not rank on *IU* within each of the long and short positions – the proportions are not forced to equal 20%, as would be the case if we ranked on *IU* within each of the positions. Table 4, panel B reports summary information about the mean percentage of securities in each of the long and short positions classified as Low *IU* and High *IU*. Within the extreme anomaly portfolios, the incidence of High *IU* securities (19.8% to 28.3%) is significantly greater than the incidence of Low *IU* securities (11.1% to 19.2%), with t-statistics of 5.90 or larger. However, in no case is the incidence of Low *IU* securities trivial.

On the whole, we believe the results in Table 4 provide strong evidence that information uncertainty is concentrated in extreme portfolios formed on the basis of signed realizations of investment signals (Hypothesis 2). That is, regardless of whether the signal is adverse or favorable, extreme values of the signal are associated with high information uncertainty.

Our tests of Hypothesis 3 examine the abnormal returns to securities classified as Low *IU* versus High *IU* in each long, short, and long-short position. We predict that positions in High *IU* securities generate larger (in magnitude) abnormal returns than positions in Low *IU* securities. Recall from Table 4, Panel B, that while there is a greater incidence of High *IU* securities in the extreme anomaly portfolios, in no case is the incidence of Low *IU* securities trivially small. Consequently, there is meaningful cross-sectional *IU* variation to explore within the extreme anomaly portfolios. Table 5 shows the mean CAPM, three-factor, and four-factor abnormal returns to High *IU* and Low *IU* securities in each of the long, short, and long-short positions of each anomaly; these abnormal returns are based on calendar-time portfolio regressions (similar to Table 2, equations 2a-f) estimated separately for Low *IU* and High *IU* securities. We also examine the difference in anomaly abnormal returns between High *IU* and Low *IU* securities (*HL*), as captured by the intercepts in equations (4a-4c):

$$(R_L - R_S)_m^{HighIU} - (R_L - R_S)_m^{LowIU} = \alpha_{LS,HL}^{CAPM} + \beta_{LS,HL} RMRF_m + \varepsilon_{LS,HL,m}^{CAPM} \tag{4a}$$

$$(R_L - R_S)_m^{HighIU} - (R_L - R_S)_m^{LowIU} = \alpha_{LS,HL}^{3f} + b_{LS,HL} RMRF_m + s_{LS,HL} SMB_m + h_{LS,HL} HML_m + \varepsilon_{LS,HL,m}^{3f} \tag{4b}$$

$$\begin{aligned}(R_L - R_S)_m^{HighIU} - (R_L - R_S)_m^{LowIU} = \alpha_{LS,HL}^{4f} &+ b_{LS,HL} RMRF_m + s_{LS,HL} SMB_m + h_{LS,HL} HML_m \\ &+ m_{LS,HL} PM_m + \varepsilon_{LS,HL,m}^{4f}\end{aligned} \tag{4c}$$

Results for the PEAD strategy show that the High *IU* combined long-short position earns 76 to 108 bp per month (depending on the model of expected returns) compared to -20 to 2 bp per month for the Low *IU* portfolio; the 93-128 bp per month difference is significant at the 0.001 level (all significance levels in the text are reported one-sided to be consistent with the one-sided hypotheses). Regardless of the asset pricing model, there is no measurable PEAD for Low *IU* securities. For the value-glamour strategies, abnormal returns to the book-to-market strategy are 67-118 bp per month for High *IU* versus -1 to 49 bp for Low *IU*. The difference of 68-69 bp per month is significant at the 0.001 level. For the cash flow-to-price specification, monthly abnormal return differences are 42-52 bp, and are significant at the 0.01 level. The difference in abnormal returns is less pronounced for the earnings-price strategy, where we find that the abnormal returns to High *IU* exceed the abnormal returns to Low *IU* by 27-33 bp per month (t-statistics range between 1.59 and 1.78). In some specifications of value-glamour anomalies (especially for CAPM abnormal returns), there are still significant abnormal returns also to Low *IU* securities. However, in all cases the abnormal returns are lower for Low *IU* securities than for High *IU* securities. Finally, results for the accruals anomaly generally show larger abnormal returns to High *IU* securities than to Low *IU* securities; differences are 21-40 bp per month. The statistical significance of the difference is inconsistent across models of expected return, however, ranging from a t-statistic of 0.84 for the CAPM to a t-statistic of 2.06 for the four-factor model.

To assess the sensitivity of the results in Table 5 to cell sample sizes (which vary given the unbalanced nature of the test), we repeat the analyses using a balanced design. The balanced design ranks observations *within* each anomaly long and short position based on *IU* and forces 20% of the securities in each anomaly quintile into each *IU* quintile. While this approach ensures that no cell has too few observations to meaningfully estimate the abnormal return, it may also induce cross-sectional differences in information uncertainty where none exist; this would bias against finding differences between the abnormal returns to High *IU* and Low *IU* securities. Results of the balanced design, reported in Table 6, are similar to the results reported in Table 5. We continue to find that within the extreme portfolios High

IU stocks tend to earn larger long-minus-short abnormal returns than Low *IU* stocks. The balanced design shows larger differences in abnormal returns between High *IU* and Low *IU* stocks for the earnings-price strategy (differences are now between 48 and 55 bp per month, with t-statistics ranging from 2.40 to 3.09); however, differences in abnormal returns to the accruals strategy are smaller (14-32 bp per month, t-statistics of 0.73 to 1.26).

Overall, we interpret the results in Tables 5 and 6 as consistent with the third hypothesis, which posits a positive relation between information uncertainty and anomaly profitability. Results are not sensitive to the use of CAPM, three-factor, or four-factor returns as the benchmark, but, in general, results are weak for the accruals anomaly.[16]

Information uncertainty also implies over-time patterns in abnormal returns. Specifically, the difference in abnormal returns between High *IU* and Low *IU* securities should diminish over time, as the information uncertainty about High *IU* stocks is resolved (Hypothesis 4).[17] Figure 2 illustrates this hypothesis (and preliminarily indicates its empirical validity) for the book-to-market strategy, using the four-factor model of expected returns. The Y-axis represents the monthly abnormal return to the long-minus-short position and the X-axis represents the period (month) after the portfolio is formed. The graph shows how the monthly abnormal return to the book-to-market portfolio evolves as one moves further away from the portfolio formation date. The abnormal returns to High *IU* securities (top line in Figure 2) trend downward much more sharply than the abnormal returns to Low *IU* securities (bottom

[16] In section 2.1, we argued that there is an unambiguous prediction of positive subsequent price movements for favorable High *IU* signals (because both the learning effect and the risk effect predict positive price movements); in contrast, there is a muted effect for unfavorable High *IU* signals (where the learning effect predicts a downward trend and the risk effect predicts an upward trend). Consistent with these arguments, we note that most specifications of the trading strategies show that the absolute value of the abnormal returns to High *IU* signals are larger for the long position (i.,e., favorable signals) than they are for the short position (i.e., unfavorable signals). The exception is the accruals strategy where the profitability of the long position is smaller in absolute value than the profitability of the short position.

[17] This prediction is related to Freeman and Tse's [1989] finding, in the context of post earnings announcement drift, of price reactions to subsequent news that directionally confirm the initial earnings signal. In contrast to Freeman and Tse, we do not specify how information uncertainty is resolved; rather, we posit cross-sectional differences in over-time abnormal returns behavior because uncertainty is resolved to different extents for High IU versus Low IU securities.

line). The trend line for High *IU* securities converges to the trend line for Low *IU* securities about 33-35 months after portfolio formation.

To formally test Hypothesis 4, we first calculate abnormal returns to the Low *IU* and High *IU* securities for the combined long-short position of each anomaly, starting *h* periods after the signal. We incrementally lag the portfolio formation signal one period, such that *h* takes on the value 1, 2, 3,…, 36 months (or 12 quarters for the post-earnings announcement drift strategy). Note that this is fundamentally different from three-year cumulative or buy-and-hold abnormal returns, which inform about the *average* or *total* abnormal return over three years. In this test, we are interested in how the monthly (quarterly) abnormal return evolves month-by-month (quarter-by-quarter) following the signal. We denote the CAPM-based abnormal returns to High *IU* and Low *IU* securities in each position as $\alpha_{LS,h}^{CAPM}(HighIU)$ and $\alpha_{LS,h}^{CAPM}(LowIU)$, respectively; three-factor abnormal returns are denoted $\alpha_{LS,h}^{3f}(HighIU)$ and $\alpha_{LS,h}^{3f}(LowIU)$, and four-factor returns as $\alpha_{LS,h}^{4f}(HighIU)$ and $\alpha_{LS,h}^{4f}(LowIU)$. The subscript *h* indexes each non-overlapping period, measured relative to the date the portfolio is formed; for the PEAD strategy, we set *h*=1,2,…,12 quarters, and for the value-glamour and accruals strategies, we set *h*=1,2,…,36 months. For example, for PEAD, $\alpha_{LS,h=3}^{CAPM}(HighIU)$ is the mean monthly CAPM abnormal return to High *IU* securities in the third quarter (months 7-9) following the portfolio formation quarter.

Relative to High *IU* securities, there is less information uncertainty to be resolved for Low *IU* stocks; therefore, as *h* increases, we expect the abnormal returns to Low *IU* securities to decline slightly or to remain constant. In contrast, we expect the abnormal returns to High *IU* securities to unambiguously decline as *h* increases. We test whether the difference between High *IU* and Low *IU* securities' abnormal returns, $\alpha_{LS,h}^{k}(HighIU)-\alpha_{LS,h}^{k}(LowIU)$, $k \in [CAPM, 3f, 4f]$, declines as *h* increases. Results are shown in Table 7, where we report coefficient estimates and t-statistics associated with regressions of anomaly abnormal returns to High *IU* securities, Low *IU* securities, and the difference, High *IU*-Low *IU*, on *h*.[18] Although the statistical power of this test is limited by the small number of observations (12 observations for PEAD and 36 for the other anomalies), the results are generally consistent with Hypothesis 4. For all anomalies and all models of expected return, the difference between High and Low *IU* securities' abnormal return decreases with *h*; that is, the more time elapses between portfolio formation and abnormal returns measurement, the smaller the *IU* effect. This trend is statistically significant in all cases except for the four-factor abnormal return for the earnings-to-price abnormal return. On balance, we interpret the evidence in Table 7 as consistent with Hypothesis 4.

3.3. <u>Summary of main results</u>

Overall, the results in Tables 3-7 suggest an association between information uncertainty and returns to trading strategies. Consistent with Hypothesis 1, we find more muted immediate market reactions to higher information uncertainty earnings signals. Consistent with Hypothesis 2, we find that the extreme portfolios formed on signed magnitudes of signals are characterized by significantly higher average information uncertainty and a disproportionate percentage of High *IU* securities. Consistent with Hypothesis 3, we find that within a given anomaly portfolio, High *IU* securities generally have significantly larger (in absolute magnitude) abnormal returns than Low *IU* securities. Finally, consistent with greater resolution of information uncertainty for High *IU* securities (Hypothesis 4), we find a declining difference between High *IU* and Low *IU* abnormal returns, as the magnitude of the abnormal returns to High *IU* securities converges to that of Low *IU* securities.

4. The Relation Between Information Uncertainty and Idiosyncratic Volatility

As mentioned in section 2, prior research has investigated whether conditioning variables (other than *IU*) can distinguish between more or less profitable exploitation of asset pricing anomalies. Conditioning variables studied include firm size, institutional ownership, analyst following, forecast heterogeneity and accuracy, and idiosyncratic returns volatility. Lakonishok, Shleifer and Vishny [1994,

[18] To ensure that calendar time (as opposed to event time) is constant across *h*, we exclude the returns for the first three years; that is, we do not want the January 1972 return (for example) to influence *h*=1 returns, but not *h*=36 returns. Our results are not sensitive to this adjustment.

section III.B] argue that several theories predict that anomalies should be less pronounced (i.e., less profitable to exploit) for large firms than for small firms – because larger firms are of greater interest to institutional investors, larger firms are more closely monitored, and larger firms suffer less from look-ahead bias and survivorship bias. Testing for such a size effect for value-glamour strategies, Lakonishok et al. reject the size hypothesis, concluding that firm size does *not* matter for the profitability of these anomalies. For the accruals anomaly, Ali, Hwang and Trombley [2000] report a similar finding with respect to size, analyst following, institutional ownership, and measures of transaction costs. Collins, Gong and Hribar [2003] show, however, that certain classes of institutional ownership have predictive power over the profitability of the accruals anomaly. Finally, building on Shleifer and Vishny [1997], Ali, Hwang and Trombley [2003], Mendenhall [2005] and Jiang, Lee and Zhang [2004] test whether limits to arbitrage (as proxied by idiosyncratic returns volatility) explain the persistence of asset pricing anomalies. They find that sorting on idiosyncratic volatility produces meaningful differences in the profitability of the book-to-market anomaly (Ali et al.), PEAD (Mendenhall) and earnings momentum (Jiang et al.), with higher levels of idiosyncratic volatility yielding higher anomaly returns than lower levels.[19]

We conclude from this research that the empirical evidence is relatively inconclusive with respect to whether and which ex-ante variables predict anomaly profitability. The main exception is idiosyncratic returns volatility, which has been shown to yield non-trivial effects in both settings where it has been

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[19] Ali et al. also document that a measure of investor sophistication (analyst following) and a measure of transaction costs have predictive power for the book-to-market anomaly; however, they report that these effects are weaker, both in magnitude and statistical significance, than the effects associated with idiosyncratic volatility. Mendenhall [2005] reports that institutional ownership and analyst following do not predict differential profitability of PEAD; he further shows that while trading volume predicts differential profitability, it does so to a lesser extent than idiosyncratic volatility. Jiang et al. also document that a firm's trading volume, listing age and equity duration have predictive power over earnings momentum profitability. We note that while Jiang et al. refer to their proxy variables as information uncertainty, they explicitly state (p.11, note 12) that the economic construct they have in mind (as well as their empirical measures thereof) bears little resemblance to our notion and measures of information uncertainty. Other studies that document variables with predictive power for PEAD include Bernard and Thomas [1989], Liang [2003] and Lu [2004]. Bernard and Thomas document that smaller firms have greater PEAD, Liang finds that PEAD is negatively related to the change in analysts' forecast accuracy, and positively related to forecast heterogeneity (measured as the correlation in forecast errors across all analysts following a firm). Lu reports that firm-specific returns volatility and abnormal trading volume (both measured over a 3-day window around the earnings announcement) have predictive power for the profitability of PEAD.

tested: the book-to-market anomaly and PEAD. This finding is of particular interest to us, because, as O'Hara [2003, pp.1349-50] points out, information risk can provide an explanation for *why* idiosyncratic volatility matters in asset pricing studies. That is, idiosyncratic volatility may be a *result* of idiosyncratic risk, which is itself driven by information uncertainty. Our tests of whether *IU* is a more primitive construct than idiosyncratic volatility proceed in three steps. First, we correlate *IU* with idiosyncratic volatility to gauge the degree of overlap between the two constructs. Second, we repeat our tests of the differential profitability of anomalies (Tables 5 and 6) using high versus low idiosyncratic volatility as the partitioning variable. These tests allow us to benchmark our *IU* results to results based on idiosyncratic volatility as the conditioning variable. Third, we orthogonalize idiosyncratic volatility with respect to information uncertainty and examine whether profitability differences persist for the orthogonalized idiosyncratic volatility measure.

Our measure of idiosyncratic volatility follows Ali, Hwang and Trombley [2003] who use the standard deviation of the residuals from regressions of daily stock returns on value-weighted market returns as their measure of idiosyncratic volatility, *IdVol*. We perform this calculation by firm and fiscal year (we require at least 100 daily returns; however, results are not sensitive to this requirement). Results (not reported) are nearly identical if we use the simple standard deviation of returns. The correlation between *IU* and *IdVol* is 0.414 (Pearson) and 0.496 (Spearman); both correlations are significant at the .001 level (not reported in tables).

In Table 8, the columns labeled "High *IU* – Low *IU*" report the differential anomaly profitability for High *IU* versus Low *IU* securities (these are the same values as reported in Table 6; we report them to facilitate comparisons). For brevity, we report only four-factor model results using the balanced design; results for CAPM and the three-factor results are similar, as are results using the unbalanced design. The columns labeled "High*IdVol* – Low*IdVol*" show the differential profitability of each trading strategy using *IdVol* as the conditioning variable. For PEAD, the *IdVol* effect is slightly larger in magnitude than the *IU* effect, but is weaker in statistical significance. The *IdVol* effect is about 20% larger than the *IU* effect for the book-to-market anomaly, whereas *IdVol* has no measurable effect for the cash flow-to-price and earnings-to-price anomalies. For the accruals anomaly, the *IdVol* effect is slightly larger than the *IU* effect. On the whole, the results indicate that the *IU* effect on anomaly profitability is roughly of the same magnitude as (or is larger than) the *IdVol* effect. We note, however, that the *IU* effect is consistent across anomalies, while the *IdVol* effect is not.

Our third and main test orthogonalizes idiosyncratic volatility with respect to information uncertainty by regressing *IdVol* on *IU*. We use the firm-year specific residuals from this regression, *ResIdVol*, as our measure of idiosyncratic volatility purged of the effects of information uncertainty. The columns labeled "High*ResIdVol* – Low*ResIdVol*" report the results of conditioning the profitability of each anomaly on *ResIdVol*. If *IU* fully (partially) explains the *IdVol* effect, we expect *ResIdVol* to produce no (lower) spread in anomaly profitability. With the exception of the book-to-market anomaly, the results are consistent with this prediction: the *IdVol* effect for PEAD declines by about 50%; for the cash flow-to-price and earnings-price anomalies there was virtually no *IdVol* effect to explain (however, the insignificant effect of *IdVol* is further reduced); and for the accruals anomaly, the *IdVol* effect is reduced by about 90%. For the book-to-market anomaly, however, the *IdVol* effect is not weakened (and, in fact, it is marginally enhanced).

In summary, consistent with prior research we find a significant idiosyncratic volatility effect on the profitability of the book-to-market anomaly and on PEAD. However, the *IdVol* effect is non-existent for the cash flow-to-price and the earnings-to-price anomalies. In contrast, the *IU* effect exists for all anomalies. In general, the *IdVol* effect is substantially reduced, or eliminated, when we control for the information uncertainty part of volatility. This finding is consistent with O'Hara's [2003] arguments suggesting that asset pricing phenomena related to idiosyncratic volatility may be explained by (idiosyncratic) information risk. We hasten to add that our findings here apply only to the abnormal returns documented in anomaly research – our tests do not speak to the relations between *expected* returns, idiosyncratic volatility and information uncertainty.

Finally, we note that our interpretation of the results does not contradict Shleifer and Vishny's [1997] arguments concerning limits to arbitrage. If information uncertainty is perceived as risky by the marginal investor,[20] then *IU* may very well be thought of as a limit to arbitrage *if* one defines arbitrage as the potential gains to trading on signals from asset pricing anomalies. Our assertion is that the fact that an anomaly is not instantaneously traded away may be a *rational* response to information uncertainty. Thus, we take issue with interpretations of idiosyncratic volatility effects as evidence of investor irrationality.

5. Additional Tests

We perform several sensitivity checks on the results. Because none of these tests has a qualitative effect on the results, we summarize, but do not tabulate, the findings from each analysis.

<u>Firm size:</u> Our first test considers firm size as an alternative explanation for the results. For Hypothesis 1, we already include size (our results are not sensitive to using total assets, sales revenues or market value of equity as the proxy for firm size) as a control variable in the cross-sectional tests (Table 3). We confirm that the inclusion of size does not affect the *IU* effect. For our main tests (of the profitability of trading strategies conditional on *IU*), we note that prior research finds mixed evidence as to whether size influences the returns to trading strategies: firm size does not distinguish between high and low anomaly profitability for the value-glamour anomalies (Lakonishok, Shleifer and Vishny [1994]) or for the accruals anomaly (Ali, Hwang and Trombley [2000]), but does for PEAD (Bernard and Thomas [1989]).

To address concerns about the sensitivity of anomaly profitability to firm size, we follow Lakonishok et al. [1994], and repeat our tests on size-partitioned samples. We find no evidence that our results are driven by small firms: (i) the U-shaped pattern in information uncertainty measures across anomaly deciles is observed (with similar statistical significance) for small, medium and large firms for all anomalies; and (ii) differences in long-short abnormal returns between the Low *IU* and High *IU*

[20] Note that analytical results in Easley and O'Hara [2004] and Leuz and Verecchia [2004], as well as empirical results in Easley, Hvidkjær and O'Hara [2002] and Francis, LaFond, Olsson and Schipper [2005], show that the cost of capital is positively associated with measures of information risk and information uncertainty. Under the standard interpretation of the cost of capital, these results imply that the marginal investor *does* perceive high information uncertainty securities to be risky.

securities of the extreme anomaly deciles are not confined to, nor are they necessarily the largest for, small firms.[21]

Value-weighted portfolios: Related to size is whether the results are robust to value-weighted portfolios (where, by construction, larger firms have more influence). The (initial) equal-weighted design was chosen for comparison with prior studies' results, which, in most case, uses equal-weighted designs (uniformly so for PEAD and the accruals anomaly, and often, but not always, for the value-glamour anomalies). The choice is not uncontroversial: Fama [1998] argues that for anomaly effects to have universal validity they must stand up to value-weighting; Loughran and Ritter [2000] disagree.

We replicate our main returns tests (Tables 5 and 6) using a value-weighted design. Specifically, like Fama and French [1993] we value-weight returns within each left-hand side portfolio. Compared to the equal-weighted design, value-weighted *IU* results are larger in magnitude, but similar in statistical significance, for all anomalies except the three- and four-factor abnormal returns to the book-to-market anomaly. The lower value-weighted effect for the latter has (at least) two potential explanations: the *IU* explanation is not robust to value-weighting, or the original anomaly is not robust to value-weighting (i.e., there is no anomaly to explain in the first place when using a value-weighted design). Probing the second explanation, we confirm that there is no book-to-market anomaly when returns are value-weighted. We conclude that when there is an anomaly to explain, information uncertainty explains its profitability, and that this result holds for both equal-weight and value-weighted designs.

Growth*:* It is unlikely that *IU* proxies for growth. If it did, we would observe linear, not U-shaped, patterns across portfolios ranked on the value-glamour variables (such as book-to-market, which is often used as a proxy for growth). Further, the pairwise correlations between *IU* and proxies for growth, other than value-glamour ratios (such as five-year compounded annual growth in sales revenues or in book

[21] Further evidence that our results are not driven by firm size is suggested by the fact that: (i) we draw similar inferences from CAPM abnormal returns as we do from abnormal returns based on the three-factor and four-factor models, which include a size-mimicking factor (*SMB*) as a control variable; and (ii) the requirement of seven years of data to estimate the *IU* metric effectively eliminates young (small) firms from the sample.

values of equity) are small (Pearson correlations are less than 0.01 in magnitude, not reported). Such small correlations are inconsistent with the view that information uncertainty is a manifestation of prior studies' finding of larger drifts in stock prices for stocks with high past growth (Lakonishok, Shleifer and Vishny [1994]).

Alternative measure of information uncertainty: Our next sensitivity test considers an alternative measure of accounting information uncertainty that does not rely on a time-series of data. Consequently, unlike our main *IU* measure, the alternative measure does not incorporate information about the over-time volatility of unexplained accruals. Our alternative measure is based on abnormal accruals estimated from the Jones [1991] model as modified by Dechow, Sloan and Sweeney [1995]. This metric measures the uncertainty in earnings as the extent to which accruals are well captured by fitted values obtained by regressing total accruals on the change in revenues and property, plant and equipment:

$$\frac{TA_{j,t}}{Asset_{j,t-1}} = \kappa_1 \frac{1}{Asset_{j,t-1}} + \kappa_2 \frac{\Delta Rev_{j,t}}{Asset_{j,t-1}} + \kappa_3 \frac{PPE_{j,t}}{Asset_{j,t-1}} + \varepsilon_{j,t} \tag{5}$$

where $Asset_{j,t-1}$ = firm j's total assets (Compustat #6) at the beginning of year t,
$\Delta Rev_{j,t}$ = firm j's change in revenues (Compustat #12) between year t-1 and year t,
$PPE_{j,t}$ = firm j's gross value of property plant and equipment (Compustat #7) in year t.

The industry- and year-specific parameter estimates obtained from equation (5) are used to estimate firm-specific normal accruals (as a percent of lagged total assets),

$NA_{j,t} = \hat{\kappa}_1 \frac{1}{Asset_{j,t-1}} + \hat{\kappa}_2 \frac{(\Delta Rev_{j,t} - \Delta AR_{j,t})}{Asset_{j,t-1}} + \hat{\kappa}_3 \frac{PPE_{j,t}}{Asset_{j,t-1}}$, where $\Delta AR_{j,t}$ = firm j's change in accounts receivable (Compustat #2) between year t-1 and year t. Abnormal accruals, $AA_{j,t}$, in year t are the difference between total accruals and normal accruals, $\frac{TA_{j,t}}{Asset_{j,t-1}} - NA_{j,t}$. Based on results in Kothari, Leone and Wasley [2005], we adjust the abnormal accruals measures for firm performance, as proxied by return on assets. Performance-adjusted abnormal accruals are calculated as the difference between firm j's $AA_{j,t}$ and the median value of $AA_{j,t}$ for its industry ROA decile. Because both large negative and large positive performance-adjusted abnormal accruals reflect a poor mapping of earnings into cash flows, we use the absolute value of this measure, $\left|AA_{j,t}\right|$, as our second information uncertainty metric. We repeat all tests using $IU_{j,t} = \left|AA_{j,t}\right|$. In all cases, we draw qualitatively similar inferences as we do using $IU = \sigma(\hat{v})$.

Alternative measure of unexpected earnings: Tests based on earnings surprises (the Table 3 tests of the short-term market response to unexpected earnings, and the PEAD tests) require a measure of expected earnings. Our main tests use analysts' forecasts to proxy for expected earnings; we also repeat our tests using a seasonal random walk (SRW) forecast. The SRW earnings surprise is the difference between firm j's reported earnings before extraordinary items for quarter q and firm j's four-quarter ago reported earnings (divided by the number of shares used to calculate earnings per share), divided by share price 20 days prior to the earnings announcement. Because SRW forecasts are available for a longer time period and for more firms, sample size increases for the SRW tests. Results based on this measure are similar to results using the analyst-based measure.

Mechanical explanations*:* Tables 5 and 6 show that abnormal returns to trading strategies are greater for High *IU* firms. One potential (mechanical) explanation for this finding is that High *IU* securities also have the most extreme realizations of the anomaly measures (earnings surprise, book-to-market ratio, etc.). Tests show, however, that the High *IU* securities within the extreme anomaly deciles do not have higher (or lower) mean values of the anomaly variable in the long (or short) position; in fact, if anything, the average effect is the opposite.

Summary: Sensitivity tests show that our results are not driven by the choice or specification of the proxy variables for information uncertainty, nor are the results driven by these proxies capturing firm size or growth effects In addition, results are not sensitive to portfolio aggregation method, or the choice of the benchmark for measuring expected returns (CAPM, three-factor, or four-factor models). We note that individual results with respect to the *underlying anomaly* are sensitive to specification; however, in each case when there is an underlying anomaly to explain, information uncertainty has explanatory power with respect to the profitability of that anomaly.

6. Conclusions

A substantial body of work in accounting and finance documents long-term abnormal returns following publicly-available investment signals. Research characterizes these returns as anomalous, because implementable trading strategies can be developed to exploit these signals. While there is debate about the proper risk adjustment for evaluating the profitability of such strategies, all of the strategies we investigate (post earnings announcement drift, value-glamour, and accruals strategies) yield significant abnormal returns as measured against the CAPM, the three-factor model, and the four-factor model. We link these anomalies to predictions derived from rational learning models in which investors rationally place less weight on signals characterized by high information uncertainty. We proxy for information uncertainty by the degree to which earnings map into fundamentals; weak mappings imply poor quality earnings (high information uncertainty), while strong mappings imply good earnings quality (low information uncertainty).

Consistent with rational investors placing less weight on noisier signals when they are announced, we find significantly weaker market reactions to unexpected earnings associated with higher information uncertainty. Examination of the characteristics of anomaly portfolios shows that extreme portfolios of the ranked signals have significantly higher average information uncertainty, and a significantly greater incidence of securities with high information uncertainty, than do non-extreme portfolios. We also show that within the extreme portfolios shown to generate significant abnormal trading returns, most of the abnormal return is concentrated in stocks with high information uncertainty. We further show that the abnormal returns associated with signals that are extreme in magnitude and high in information uncertainty converge over time to the abnormal returns of extreme magnitude but low information uncertainty securities, consistent with resolution of the uncertainty about the signal. Finally, we link our findings concerning information uncertainty with prior studies' evidence concerning idiosyncratic volatility. Building on O'Hara's [2003] arguments that asset pricing phenomena related to idiosyncratic volatility may be explained by idiosyncratic information risk, we test whether the information uncertainty effects we document explain prior studies' findings that idiosyncratic volatility predicts the profitability of trading strategies. Results generally show that the idiosyncratic volatility effect is reduced, or eliminated altogether, when we control for the portion of idiosyncratic volatility that is associated with information uncertainty.

Taken as a whole, our results indicate that abnormal returns are systematically associated with measures of the quality of the firm's information environment — that is, with information uncertainty. We view these findings as being consistent with a rational explanation for the existence of abnormal returns to investment signals: investors place lower weights on investment signals of lower precision, and revise those weights as uncertainty about the signal is resolved. Because it is not always possible to distinguish between this rational explanation and competing irrational explanations (Brav and Heaton [2002]), we cannot definitively conclude whether investors' rational responses to information uncertainty or their irrational cognitive biases offer a more convincing explanation for the existence of accounting anomalies. We are not aware, however, of any behavioral explanation for our results; that is, we know of no reason why a cognitive bias that is consistent with under-reaction (such as conservatism) would also vary cross-sectionally with information uncertainty. Moreover, recent work by Chan, Frankel and Kothari [2003] finds no support for the view that cognitive biases explain accounting anomalies.

Appendix: Overview of Accounting Anomalies, Construction of Accounting Signals and Implementation of Accounting-Based Trading Strategies

In this section, we describe, and review prior findings about, the accounting anomalies that we investigate in our study.[22] Following each description, we detail the calculation of the accounting signal(s) that forms the basis for the strategy and we summarize the procedures used to implement the calendar-time-portfolio regressions used to assess the statistical significance of the abnormal returns to the trading strategy.

A.1. <u>Post earnings announcement drift (PEAD)</u>

PEAD is arguably the most well-documented and most robust of the anomalies, showing consistent evidence of abnormal returns across time periods, samples, and measures of earnings surprise. Bernard and Thomas [1989; 1990] and Bernard, Thomas and Wahlen [1996] also show that PEAD is robust to a battery of risk adjustments. Several papers interpret PEAD as a failure by the market to fully appreciate the implications of current earnings for future earnings (e.g., Abarbanell and Bernard [1992], Chan, Jegadeesh, and Lakonishok [1996]). In a general discussion of earnings-based anomalies, Ball [1992] argues that PEAD is due to some combination of information-processing costs and market inefficiency.

Taking positions based on post earnings announcement drift requires information about the earnings announcement date and the earnings surprise in firm j's quarter q earnings announcement. We use Compustat earnings announcement dates, and we calculate earnings surprises using Zacks analysts' earnings forecasts. (As mentioned in section 5, we also calculate earnings surprises using a seasonal random walk (SRW) specification, with qualitatively similar results). The earnings surprise equals the difference between firm j's reported earnings per share before extraordinary items (Compustat #19) for

[22] Research also suggests some overlap among anomalies. For example, Fama and French [1996] show that a combination of book-to-market and size overlaps with the cash flow-to-price and earnings- price anomalies. Desai, Rajgopal and Venkatachalam [2004] show that the accruals anomaly overlaps with a cash flow-to-price strategy. Our research design treats each anomaly as distinct, and investigates the extent to which each of them is separately associated with information uncertainty. Hence, our results for the five anomalies should not be interpreted as independent tests.

quarter q and the consensus median analyst forecast of firm j's quarter q earnings, divided by firm j's share price 20 days prior to the earnings announcement. The consensus median forecast is the median forecast for the quarter made by all analysts following firm j; in forming the consensus, we use only the last forecast made by each analyst prior to the earnings announcement.

Each calendar quarter, we rank firms into deciles based on the earnings surprise. We take long positions in the 20% of stocks with the most positive earnings surprises and short positions in the 20% of stocks with the most negative surprises. Firms enter the portfolio on the first day of the calendar quarter following the earnings announcement, and are held for six months. For example, if a firm announces its quarterly earnings on May 25, it enters a portfolio on July 1. We choose six months as our holding period to ensure that it includes two subsequent quarterly earnings announcements.[23] The return to the *p*'th portfolio in month *m*, $R_{p,m}$, is the mean of the equally-weighted returns across the j=1,…,J securities comprising portfolio $p \in \{Long, Short, Long - Short\}$.

A.2. Value-Glamour Strategies

Research on the returns characteristics of value versus glamour stocks has shown superior returns to investing in stocks with high book-to-market ratios, high cash flow-to-price ratios and high earnings-price ratios, relative to stocks with low values of these ratios (see Fama and French [1993] and Lakonishok, Shleifer and Vishny [1994] for overviews). While there is a debate as to whether the returns to value-glamour signals are due to risk or mispricing (e.g., Lakonishok, Shleifer and Vishny [1994], Fama and French [1996]), the empirical facts about the returns patterns are not in dispute.

The value-glamour strategies require information about share price and shares outstanding (both are obtained from CRSP) as well as accounting fundamentals: net income before extraordinary items

[23] PEAD studies measure abnormal returns over one to four quarters after the earnings announcement date (e.g., Bernard and Thomas [1989; 1990], Abarbanell and Bernard [1992], Mendenhall [2005]). We include two quarters because prior studies provide mixed evidence about whether the third and fourth quarter returns are (or are not) significantly positive. (Note that our research design focuses on longer-term abnormal returns (monthly or quarterly), not shorter-term abnormal returns (such as those in the 3-days surrounding subsequent earnings announcements). Thus, our design does not speak to prior studies tests of a fourth-quarter reversal in abnormal returns, concentrated in the 3-window around the Q4 earnings announcement (e.g., Abarbanell and Bernard [1992], who show that the 3-day negative abnormal return is more than offset by the rest of Q4's positive abnormal return, yielding a (small) positive Q4 abnormal return).

(Compustat #18), book value of equity (Compustat #60) and cash flows from operations, *CFO*. The latter is calculated, following Kothari, Leone and Wasley [2005], as net income before extraordinary items less total accruals, $TA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPN_{j,t}$, where $\Delta CA_{j,t}$ = firm j's change in current assets (Compustat #4) between year t-1 and year t, $\Delta CL_{j,t}$ = firm j's change in current liabilities (Compustat #5) between year t-1 and year t, $\Delta Cash_{j,t}$ = firm j's change in cash (Compustat #1) between year t-1 and year t, $\Delta STDEBT_{j,t}$ = firm j's change in debt in current liabilities (Compustat #34) between year t-1 and year t, $DEPN_{j,t}$ = firm j's depreciation and amortization expense (Compustat #14) in year t.

At the end of fiscal year t, the firm's accounting fundamental is divided by its market value. The accounting information is assumed to be known at the beginning of the fourth month following the firm's fiscal year end, and the value-glamour signal stays constant for that firm until the next fiscal year's signal becomes available. For example, a firm with a fiscal year end in January 1995 will have its corresponding value-glamour signal from May 1995 until April 1996. We employ a dynamic portfolio formation technique for each signal to accommodate firms with different fiscal year ends and to avoid differentially stale information (as would be the case if we rebalanced only once per calendar year). At the beginning of each month, firms are ranked into portfolios based on the distribution of all available accounting fundamental-to-price ratios for that month. Implementation choices for the construction of the portfolios generally follow Lakonishok, Shleifer and Vishny [1994]. Specifically, we require firms to have positive values of the accounting fundamental, we form deciles based on the ranked distribution of the fundamental-to-price signal and take long positions in the 20% of stocks with the largest values of the signal and short positions in the 20% with the smallest values of the signal, and we equal-weight the returns within each portfolio.

A.3. Accruals anomaly

Several studies have investigated whether investors correctly price accruals. For example, Sloan [1996] finds that a strategy that takes long positions in stocks with the most negative total accruals and short positions in stocks with the most positive total accruals earns significant positive abnormal returns. Collins and Hribar [2000] find similar results for quarterly data. Chan, Chan, Jegadeesh and Lakonishok [2001] corroborate the total anomaly. Finally, Richardson, Sloan, Soliman and Tuna [2002] show that most of the information in accruals is associated with firms experiencing changes in asset turnover, rather than growth in sales.

The accruals anomaly requires information about firm j's accruals in year t. Following Sloan [1996], the total accruals signal equals total accruals scaled by beginning-of-year total assets, $\frac{TA_{j,t}}{Assets_{j,t-1}}$. We assume that information about $\frac{TA_{j,t}}{Assets_{j,t-1}}$ is available at the beginning of the fourth month following firm j's fiscal year end; it remains the same for the following 12 months. Using the same dynamic technique as used for the value-glamour strategies, each month the accruals portfolios are rebalanced based on the distribution of the accruals metric available at the beginning of that month. We take long (short) positions in the 20% of firms with the most negative (most positive) values of $\frac{TA_{j,t}}{Assets_{j,t-1}}$, and we equal-weight returns within each portfolio.

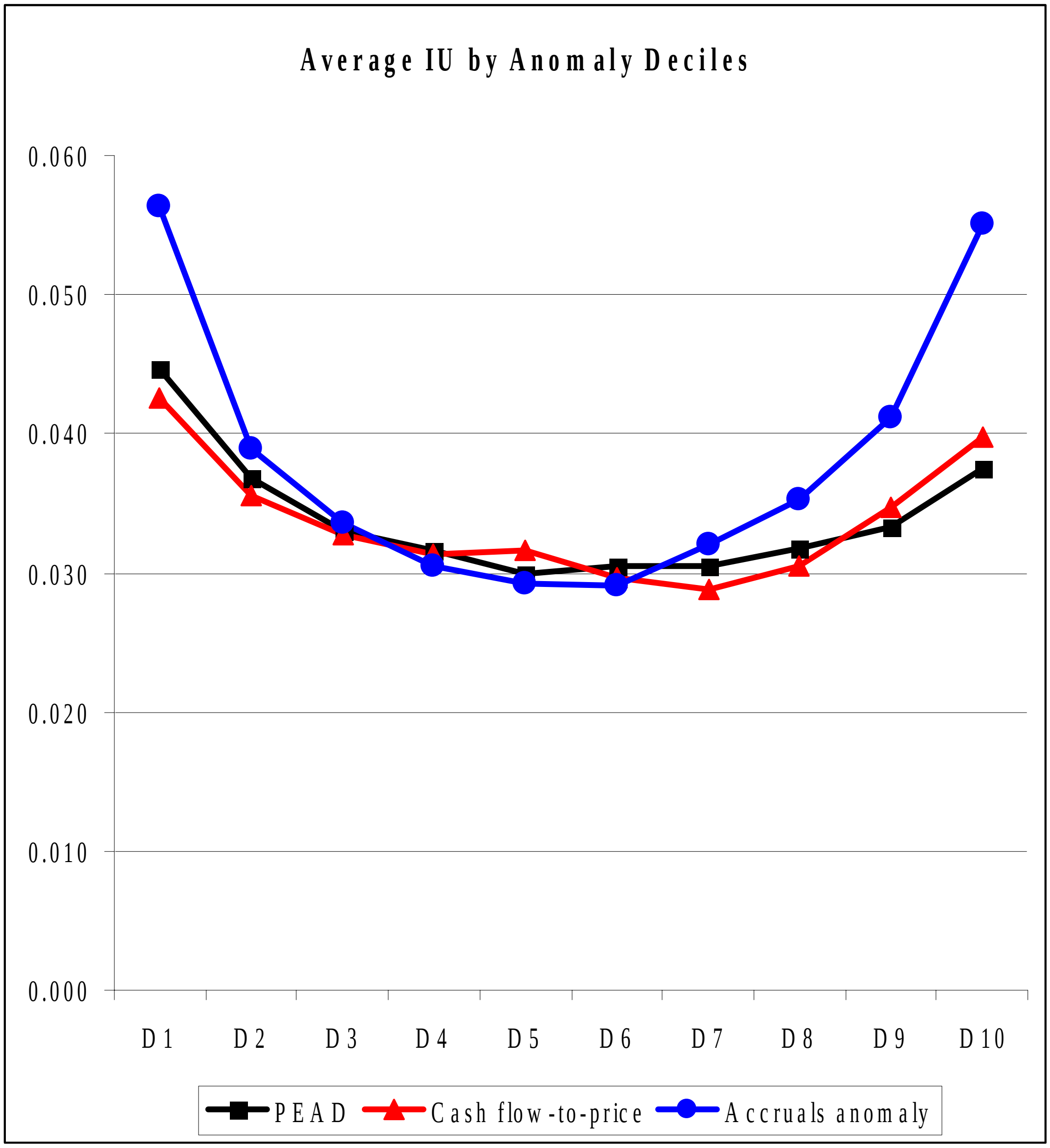

Figure 1 shows the mean value of *IU* for the ranked deciles of the post earnings announcement drift (PEAD), cash flow-to-price and accruals anomalies.

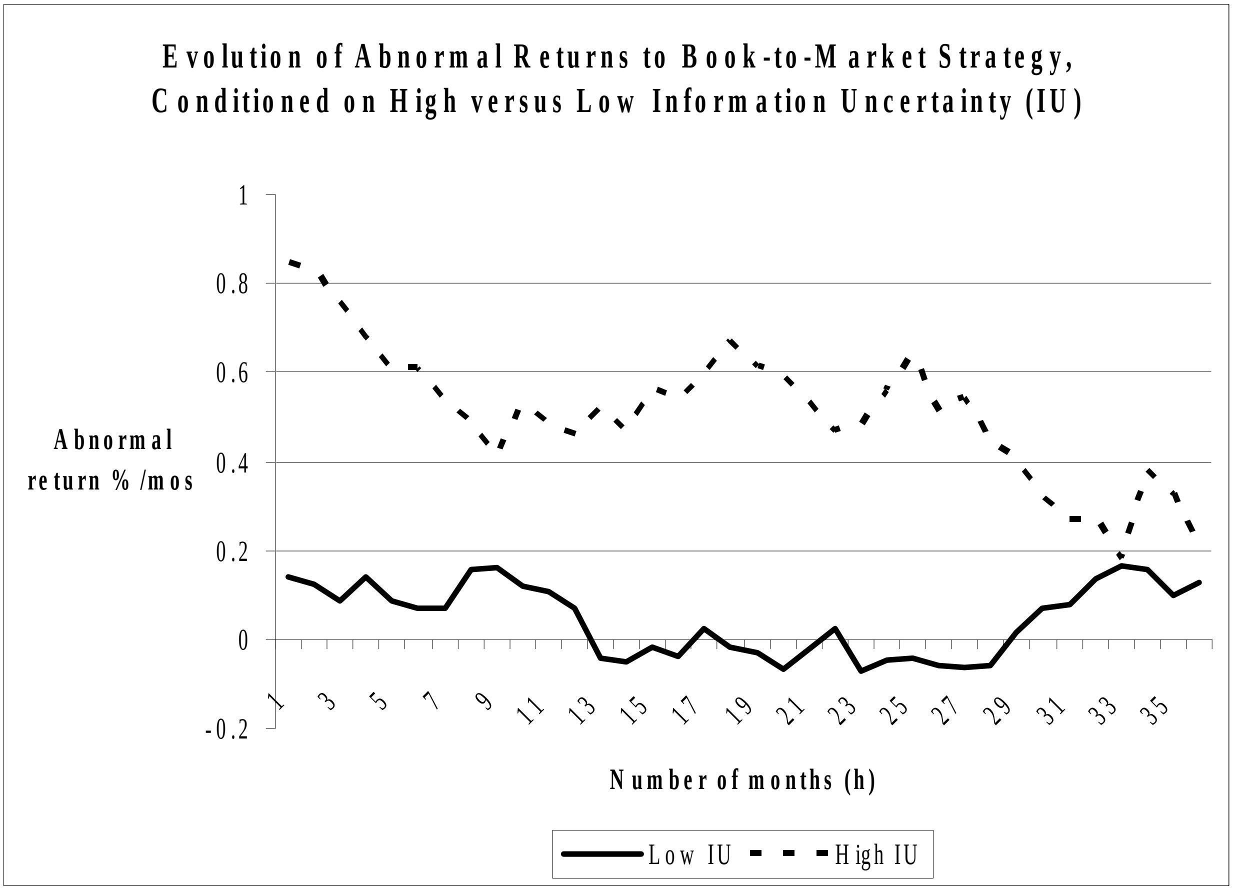

Figure 2 shows the mean abnormal return in period *h*, to the long-minus-short position in a book-to-market strategy taken at time *h*=0 in Low *IU* versus High *IU* securities. For example, the point *h*=5 represents the average abnormal return to the portfolio in the fifth month following the month in which the position was taken.

Table 1
Descriptive Statistics about Information Uncertainty Metric

Panel A: Number of firms with data on information uncertainty metric, by year

Year	# firms	Year	# firms
1970	1,094	1986	2,615
1971	1,209	1987	2,584
1972	1,301	1988	2,572
1973	1,453	1989	2,594
1974	1,857	1990	2,664
1975	2,143	1991	2,714
1976	2,311	1992	2,853
1977	2,368	1993	3,077
1978	2,425	1994	3,144
1979	2,450	1995	3,216
1980	2,562	1996	3,238
1981	2,940	1997	3,311
1982	2,907	1998	3,392
1983	2,839	1999	3,448
1984	2,804	2000	3,456
1985	2,686	2001	3,371

Panel B: Distribution of information uncertainty metric

	mean	std. dev.	10%	25%	median	75%	90%
IU	0.0403	0.0360	0.0103	0.0170	0.0292	0.0508	0.0838

Variable definitions and sample description: $IU = \sigma(\hat{v})$ is the standard deviation of the residuals from rolling five-year regressions of current accruals on lagged, current and future cash flows from operations. The *IU* sample consists of all firms with the necessary data to calculate *IU* in years t=1971-2001.

Table 2
Average Monthly Abnormal Returns to Extreme Anomaly Portfolios[a]

	Unrestricted Sample			IU Sample		
	CAPM	3-factor	4-factor	CAPM	3-factor	4-factor
PEAD						
Short (most neg. surprise)	-0.314	-0.164	0.199	-0.071	-0.075	0.177
Long (most pos. surprise)	0.403	0.499	0.645	0.554	0.366	0.526
Long-Short	0.716	0.663	0.446	0.625	0.441	0.349
t-stat. (long-Short)	6.14	5.12	3.78	3.81	3.69	2.65
Book-to-market anomaly						
Short (smallest value)	-0.641	-0.340	-0.345	-0.277	-0.079	-0.028
Long (largest value)	0.427	0.276	0.375	0.431	0.350	0.388
Long-Short	1.068	0.615	0.721	0.709	0.429	0.417
t-stat. (long-Short)	6.98	6.92	7.00	5.85	4.60	4.32
Cash flow-to-price anomaly						
Short (smallest value)	-0.276	-0.161	-0.057	-0.147	-0.059	0.067
Long (largest value)	0.590	0.456	0.532	0.583	0.466	0.530
Long-Short	0.866	0.617	0.589	0.730	0.525	0.463
t-stat. (long-Short)	8.17	8.45	7.06	7.36	6.97	5.91
Earnings-to-price anomaly						
Short (smallest value)	-0.314	-0.222	-0.188	-0.029	-0.026	0.027
Long (largest value)	0.541	0.349	0.379	0.486	0.319	0.345
Long-Short	0.855	0.571	0.568	0.515	0.345	0.318
t-stat. (long-Short)	6.95	6.24	6.19	5.14	4.05	3.57
Accruals anomaly						
Short (most positive)	-0.714	-0.500	-0.386	-0.345	-0.225	-0.148
Long (most negative)	0.042	0.186	0.224	0.366	0.448	0.551
Long-Short	0.756	0.686	0.610	0.712	0.673	0.698
t-stat. (long-Short)	8.31	7.53	6.52	10.5	9.92	9.26

Variable definitions: See Table 1.

[a] The Unrestricted Sample contains firms with monthly returns data and the necessary data to calculate each anomaly signal. The *IU* Sample includes observations with data on *IU*. For each sample, we report the average monthly abnormal return to the noted portfolio (short, long, long-short), for the period April 1971-December 2001; for PEAD the period is 1982-2001. We report abnormal returns based on the CAPM, three-factor, and four-factor models of expected returns. The abnormal return is the intercept from a calendar-time portfolio regression of each portfolio (long, short, long-short) return on *RMRF* in the CAPM regression, on *RMRF*, *SMB*, and *HML* in the three-factor regressions, and on *RMRF*, *SMB*, *HML* and *PM* in the four-factor regressions. *RMRF* is the excess market return, *SMB* is a size factor mimicking portfolio, *HML* is a book-to-market factor mimicking portfolio, and *PM* is the return to a price momentum strategy. Data on *RMRF*, *SMB*, *HML*, and *PM* are from K. French. The Appendix details the construction of each signal and the implementation of the trading strategies.

Table 3
Market Responses to Unexpected Earnings News,
Conditional on the Information Uncertainty of Earnings Signal[a]

Indep. variable	Coef.est.	t-stat.	Coef.est.	t-stat.
UE	0.1691	6.40	0.1760	6.46
*UE*DecileIU*	-0.0116	-3.40	-0.0129	-3.67
Size	--	--	-0.0003	-0.64
Leverage	--	--	0.0013	0.31
Growth	--	--	-0.0095	-1.19

Variable definitions and sample description: $UE_{j,q}$ = unexpected earnings revealed in firm j's quarter q earnings announcement. We measure *UE* using analysts' consensus forecast. *Size* = log of firm j's total assets; *Leverage* = firm j's ratio of interest bearing debt to total assets; *Growth* = firm j's percentage growth in sales between years t-1 and t.

Table 4
Information Uncertainty of Securities in Anomaly Deciles

Panel A: Mean information uncertainty of securities in anomaly deciles[a]

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Diff	t-stat	% mos diff>0
PEAD	0.045	0.037	0.033	0.032	0.030	0.030	0.030	0.032	0.033	0.037	0.007	32.12	98%
Book-to-market	0.053	0.040	0.037	0.035	0.033	0.033	0.034	0.036	0.037	0.037	0.007	29.15	99%
Cash flow-to-price	0.043	0.036	0.033	0.031	0.032	0.030	0.029	0.030	0.035	0.040	0.007	40.04	100%
Earnings-to-price	0.044	0.037	0.033	0.032	0.030	0.031	0.030	0.031	0.034	0.038	0.007	36.76	100%
Accruals anomaly	0.056	0.039	0.034	0.030	0.029	0.029	0.032	0.035	0.041	0.055	0.016	39.87	100%

Panel B: Proportion of high (low) information uncertainty securities within extreme portfolios (unbalanced design)[b]

	Low IU	High IU	Diff. (t-stat.)
PEAD	17.0%	26.3%	42.96
Book-to-market	16.2%	22.4%	37.33
Cash flow-to-price	17.3%	19.8%	16.19
Earnings-to-price	19.1%	20.4%	5.90
Accruals anomaly	11.1%	28.3%	84.58

Variable definitions: see Table 1.

[a] We report the mean value (over the 369 monthly portfolios, April 1971-December 2001; 240 months in the case of PEAD, January 1982-December 2001) of the average *IU* calculated across the securities in each anomaly decile in month *m*. The column labeled "Diff." shows the difference between the mean values of *IU* for securities in the extreme deciles (1, 2, 9 and 10) versus the moderate deciles (3-8). The t-statistic for the test of whether this difference is reliably different from zero is based on the standard error of the time series of differences. "%mos diff>0" is the fraction of months where the difference is positive.

[b] We report the fraction of total securities within the noted extreme anomaly portfolios (which comprise the short and long position) with High *IU* versus Low *IU*. Low *IU* securities are those in the bottom two deciles of the ranked distribution of the *IU* metric, while High *IU* securities are in the top two deciles. The column labeled "Diff." shows the t-statistic for whether the mean percentage of High *IU* securities is greater than the mean percentage of Low *IU* securities. The t-test of whether this difference is significant is based on the standard error of the time series of monthly differences.

Table 5
Average Monthly Abnormal Returns to High and Low Information Uncertainty Securities
Within Extreme Anomaly Portfolios: Unbalanced Design[a]

	Abnormal Returns					
	CAPM		3-factor model		4-factor model	
	Low IU	High IU	Low IU	High IU	Low IU	High IU
PEAD						
Short (most neg. surprise)	0.709	-0.507	0.230	-0.274	0.439	0.027
Long (most pos. surprise)	0.508	0.575	0.253	0.675	0.246	0.790
Long-Short	-0.201	1.083	0.023	0.949	-0.193	0.763
t-stat (Long-Short)	0.00	4.67	0.62	3.97	-1.87	3.81
Diff: High IU - Low IU	1.284	t=3.88	0.926	t=3.71	0.956	t=3.95
Book-to-market anomaly						
Short (smallest value)	0.079	-0.542	0.199	-0.315	0.265	-0.273
Long (largest value)	0.565	0.633	0.295	0.460	0.259	0.396
Long-Short	0.486	1.175	0.096	0.774	-0.006	0.669
t-stat (Long-Short)	2.77	5.93	0.40	4.20	0.00	3.94
Diff: High IU - Low IU	0.689	t=4.12	0.679	t=3.27	0.675	t=3.26
Cash flow-to-price anomaly						
Short (smallest value)	0.106	-0.383	0.113	-0.188	0.200	-0.094
Long (largest value)	0.677	0.608	0.376	0.566	0.372	0.602
Long-Short	0.571	0.991	0.263	0.754	0.172	0.696
t-stat (Long-Short)	3.83	5.76	2.29	4.63	1.47	4.13
Diff: High IU - Low IU	0.421	t=2.63	0.490	t=2.37	0.524	t=2.58
Earnings-to-price anomaly						
Short (smallest value)	0.123	-0.344	0.052	-0.184	0.120	-0.015
Long (largest value)	0.519	0.379	0.191	0.278	0.207	0.346
Long-Short	0.396	0.723	0.139	0.462	0.087	0.361
t-stat (Long-Short)	2.54	4.35	1.12	2.87	0.64	3.25
Diff: High IU - Low IU	0.327	t=1.69	0.323	t=1.59	0.274	t=1.78
Accruals anomaly						
Short (most positive)	-0.056	-0.611	-0.137	-0.498	-0.021	-0.495
Long (most negative)	0.498	0.155	0.283	0.255	0.342	0.264
Long-Short	0.554	0.766	0.420	0.753	0.363	0.759
t-stat (Long-Short)	4.91	5.10	3.97	4.76	3.04	5.10
Diff: High IU - Low IU	0.212	t=0.84	0.333	t=1.41	0.396	t=2.06

Variable definitions and sample description: see Tables 1 and 2.

[a] We report the mean monthly abnormal return to the High *IU* and Low *IU* securities within each of the extreme anomaly portfolios (short, long, long-short). Low *IU* securities are those in the bottom two deciles of the ranked distribution of the *IU* metric, while High *IU* securities are in the top two deciles. We report abnormal returns based on CAPM, three-factor, and four-factor models of expected returns.

Table 6
Average Monthly Abnormal Returns to High and Low Information Uncertainty Securities
Within Extreme Anomaly Portfolios: Balanced Design[a]

	Abnormal Returns					
	CAPM		3-factor model		4-factor model	
	Low IU	High IU	Low IU	High IU	Low IU	High IU
PEAD						
Short (most neg. surprise)	0.549	-0.470	0.308	-0.119	0.434	0.143
Long (most pos. surprise)	0.539	0.646	0.267	0.778	0.268	0.873
Long-Short	-0.010	1.116	-0.041	0.898	-0.166	0.730
t-stat (Long-Short)	-0.05	3.56	0.00	3.29	-1.24	2.89
Diff: High IU - Low IU	1.126	t=3.46	0.939	t=2.90	0.896	t=2.80
Book-to-market anomaly						
Short (smallest value)	0.056	-0.659	0.153	-0.359	0.242	-0.302
Long (largest value)	0.558	0.595	0.312	0.503	0.283	0.477
Long-Short	0.502	1.254	0.159	0.863	0.041	0.779
t-stat (Long-Short)	3.08	6.14	1.17	4.73	0.37	4.25
Diff: High IU - Low IU	0.752	t=3.83	0.704	t=3.66	0.738	t=3.76
Cash flow-to-price anomaly						
Short (smallest value)	0.031	-0.462	0.088	-0.267	0.160	-0.200
Long (largest value)	0.635	0.617	0.409	0.598	0.436	0.671
Long-Short	0.604	1.079	0.321	0.865	0.294	0.871
t-stat (Long-Short)	4.15	5.89	2.96	5.47	2.62	5.13
Diff: High IU - Low IU	0.475	t=2.64	0.545	t=2.69	0.577	t=2.66
Earnings-to-price anomaly						
Short (smallest value)	0.129	-0.419	0.065	-0.287	0.172	-0.224
Long (largest value)	0.463	0.397	0.091	0.223	0.108	0.264
Long-Short	0.334	0.817	0.026	0.509	-0.064	0.488
t-stat (Long-Short)	1.68	4.97	0.15	3.30	-0.50	3.28
Diff: High IU - Low IU	0.483	t=3.09	0.484	t=2.40	0.551	t=2.82
Accruals anomaly						
Short (most positive)	-0.164	-0.580	-0.115	-0.444	-0.067	-0.420
Long (most negative)	0.453	0.182	0.286	0.277	0.354	0.233
Long-Short	0.617	0.762	0.401	0.721	0.422	0.653
t-stat (Long-Short)	5.19	4.17	4.40	3.92	3.86	3.40
Diff: High IU - Low IU	0.145	t=0.73	0.320	t=1.03	0.231	t=1.26

Variable definitions and sample description: see Tables 1 and 2.

[a] We report the mean monthly abnormal return to the High *IU* and Low *IU* securities within each of the extreme anomaly portfolios (short, long, long-short). Low *IU* securities are those in the bottom two deciles of the ranked distribution of the *IU* metric, while High *IU* securities are in the top two deciles. In this table, the ranking of securities on *IU* is performed *within* each of the anomaly deciles; hence, equal numbers of securities are classified as having Low *IU* versus High *IU*. We report abnormal returns based on CAPM, three-factor, and four-factor models of expected returns.

Table 7
Regression of Abnormal Returns on Number of Periods Post Portfolio Formation,
For High and Low Information uncertainty Securities in Extreme Anomaly Portfolios[a]

	Abnormal Returns					
	CAPM		3-factor model		4-factor model	
	Coef. Est.	t-stat.	Coef. Est.	t-stat.	Coef. Est.	t-stat.
PEAD						
High IU	-0.055	-2.21	-0.068	-2.44	-0.074	-2.71
Low IU	0.049	2.30	0.039	2.23	0.048	2.42
High IU - Low IU	-0.104	-2.89	-0.107	-2.92	-0.122	-3.79
Book to market anomaly						
High IU	-0.025	-24.16	-0.013	-10.76	-0.011	-6.74
Low IU	-0.011	-6.70	-0.001	-0.83	-0.001	-1.08
High IU - Low IU	-0.015	-8.11	-0.012	-5.32	-0.010	-3.75
Cash flow to price anomaly						
High IU	-0.025	-8.58	-0.016	-8.21	-0.016	-7.40
Low IU	-0.004	-2.81	0.003	1.56	0.005	2.39
High IU - Low IU	-0.020	-9.85	-0.019	-13.33	-0.021	-12.35
Earnings to price anomaly						
High IU	-0.012	-4.80	-0.003	-1.44	-0.003	-0.97
Low IU	-0.004	-3.65	0.002	1.92	0.000	-0.20
High IU - Low IU	-0.008	-3.14	-0.005	-2.13	-0.002	-0.90
Accruals anomaly						
High IU	-0.015	-12.09	-0.017	-13.83	-0.021	-12.39
Low IU	-0.001	-0.30	0.003	1.44	0.005	2.64
High IU - Low IU	-0.014	-7.24	-0.020	-10.16	-0.025	-11.79

Variable definitions and sample description: see Tables 1 and 2.

[a] We report the coefficient estimate and t-statistic from regressing the abnormal return in post-portfolio formation period *h* on *h*, where *h*= 1,2, …, 12 quarters for PEAD and *h*=1,2, …, 36 months for the value-glamour and accruals strategies. The rows labeled "High *IU*" and "Low *IU*" respectively, show the results for abnormal returns to securities classified as high and low information uncertainty; the row labeled "High *IU*-Low *IU*" shows the results when the dependent variable is the difference in abnormal returns in period *h* between High *IU* and Low *IU* securities. Low *IU* securities are those in the bottom two deciles of the ranked distribution of the *IU* metric, while High *IU* securities are in the top two deciles.

Table 8
Average Monthly 4-Factor Abnormal Returns to High and Low Volatility Securities
Within Extreme Anomaly Portfolios, Balanced Design

	High IU - Low IU		*High IdVol - Low IdVol*		*High ResIdVol - LowResIdVol*	
	Diff	t-stat	Diff	t-stat	Diff	t-stat
PEAD strategies	0.896	2.800	1.014	2.500	0.540	1.390
Book-to-market	0.738	3.760	0.875	3.340	0.920	3.800
Cash flow-to-price	0.577	2.660	0.102	0.410	0.014	0.060
Earnings-to-price	0.551	2.820	0.011	0.050	-0.149	-0.640
Accruals anomaly	0.231	1.260	0.306	1.540	0.023	0.110

Variable definitions: See Tables 1 and 2. *IdVol* = standard deviation of the residuals from firm- and year-specific regressions of daily stock returns on the value-weighted market return. ResIdVol = firm-specific residual from a regression of *IdVol* on *IU*.

[a] The columns labeled "High *IU* – Low *IU*" report the differential anomaly profitability for High *IU* versus Low *IU* securities: these are the same values as reported in Table 6. The columns labeled "High *IdVol* – Low *IdVol*" show the differential profitability of each trading strategy using *IdVol* as the conditioning variable. The columns labeled "High*ResIdVol* – Low*ResIdVo*l" report the results of conditioning the profitability of each anomaly on *ResIdVol.*

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Keywords: anomalies, information uncertainty, earnings quality. JEL Classification: G14, M41, M43, D82. Financial market anomalies are cross-sectional and time series patterns in security returns that are not predicted by a central paradigm or theory. The term anomaly can be traced to Kuhn (1970). Documentation of anomalies often presages a transitional phase toward a new paradigm. Discoveries of financial market anomalies typically arise from empirical tests that rely on a joint null hypothesis â€“ to wit, security markets are informationally efficient and returns behave according to a pre-specified equilibrium model (e.g., capital asset pricing model (CAPM)). If the joint hypothesis is rejected,